EXHIBIT 13

to the Declaration of Dean M. Harvey in Support of Plaintiffs' Opposition Briefs

REDACTED VERSION

IN THE UNITED STATES DISTRICT COURT FOR THE NORTHERN DISTRICT OF CALIFORNIA SAN JOSE DIVISION

HIGHLY CONFIDENTIAL – TO BE FILED UNDER SEAL SUBJECT TO PROTECTIVE ORDER

IN RE: HIGH-TECH EMPLOYEES ANTITRUST LITIGATION	No. 11-CV-2509-LHK
THIS DOCUMENT RELATES TO:	
ALL ACTIONS	

REPLY EXPERT REPORT OF EDWARD E. LEAMER, PH.D.

December 11, 2013

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I. Introduction, Assignment, and Summary of Conclusions

- 1. I have been asked by counsel for the Plaintiffs in this case to respond to the Expert Reports of Dr. Lauren Stiroh¹ (the "Stiroh Report"), Dr. Elizabeth Becker² (the "Becker Report"), and Dr. David Lewin³ (the "Lewin Report"), to address issues they raise that were not addressed in my five previous Reports in this matter, dated October 1, 2012 (the "Leamer Report"), December 10, 2012 (the "Leamer Reply Report"), May 10, 2013 (the "Leamer Supplemental Report"), July 12, 2013 (the "Leamer Rebuttal Supplemental Report"), and October 28, 2013 (the "Leamer Damages Report"). In those prior reports I analyzed the economic effects of the Defendants' Non-Compete Agreements, the impact across Defendants' employees and the Class, estimated undercompensation to the Class and explained how and why the agreements impacted the compensation of the Defendants' workforces, including members of the Class.
- 2. Dr. Stiroh repeats many of the same errors of Dr. Murphy and I have already addressed many of the issues raised by her and the others in my prior reports and depositions. I will not repeat the contents of those reports and depositions here.
- 3. An updated version of my CV is attached as Exhibit 1. The materials I relied upon in the preparation of this report (in addition to those listed in my previous reports) are listed in Exhibit 2. Also, I reserve the right to consider any further relevant evidence that might emerge and to revise my opinions if needed.⁴

¹ Expert Report of Lauren J. Stiroh, Ph.D., November 25, 2013.

² Expert Report of Elizabeth Becker, Ph.D., November 25, 2013.

³ Expert Report of David Lewin, Ph.D., November 25, 2013.

⁴ I have been advised by counsel that a stipulation has been reached with Defendants to exclude a handful of titles from the class. I have run my analyses based on this updated data set. The exclusion of these titles does not materially impact any of the results or my conclusions.

II. Qualifications of Dr. Stiroh

- 1. I have been asked by counsel whether Dr. Stiroh is qualified to offer the criticisms she has made in her report. She is not. Dr. Stiroh testified at deposition that her expertise is based on a few statistics classes taken in college and econometrics classes taken as a Ph.D. candidate. Since obtaining her Ph.D. seventeen years ago, she has not published peer-reviewed articles on statistics, economics, or any other topic, or undertaken further formal study in the fields of statistics or econometrics. I do not think that classroom work and peer-reviewed research are the only ways to learn how properly to carry out a data analysis, and I am inclined to give Dr. Stiroh the benefit of the doubt that her experience in legal matters would be sufficient, but her work has demonstrated otherwise.
- 2. While her expertise might be sufficient in another case, it is not sufficient in this one, as demonstrated by the shallowness of her understanding of concepts such as statistical significance and standard errors. Her Exhibit V.12 reports a completely inappropriate decomposition of a nonlinear model. Her Exhibit V.14 reports a regression which imposes the assumption that there are no damages for 38 year olds, presumably without her awareness. Her suggestion that a wage regression should be calculated in nominal terms, or that the total new hires variable should be broken down into less informative variables, are similarly infirm.

III. Updated Damages

3. As noted in footnote four, I have run my analyses based on this updated data set. The exclusion of these titles does not materially impact any of the results or my conclusions. It has a minor effect on the total class compensation and the aggregate damages. The updated figures are presented in Table 1 and Table 2.

Table 1: Class Summary

		Number of	Class Employee	Total Class
Defendant	Class Period	Class Members	Years	Compensation
				(Dollars)
(1)	(2)	(3)	(4)	(5)
Adobe ¹	05/05-12/09	3,734	10,272	\$ 1,660,096,638
Apple	03/05-12/09	7,427	20,078	
Google	03/05-12/09			
Intuit	06/07-12/09	3,448	5,948	959,986,056
Lucas film ¹	01/05-12/09	521	1,324	162,436,292
Pixar	01/05-12/09	881	2,826	514,665,913
TOTAL		64,613	199,456	\$ 32,749,323,558

¹ Additional 6 Senior Executive titles excluded

Source: Defendants' employee compensation data; SEC filings.

Table 2: Class Damages Summary

		Total Class		But-For			Under-
Year	(Compensation	(Compensation	To	otal Damages	Compensation
				(Dollars)			(Percent)
							(4)/(2)
(1)		(2)		(3)		(4)	(5)
2005	\$	3,749,502,818	\$	3,886,966,863	\$	137,464,045	3.7 %
2006		5,811,762,995		6,232,713,165		420,950,170	7.2
2007		7,010,501,158		7,690,220,110		679,718,951	9.7
2008		7,385,586,926		8,273,632,367		888,045,441	12.0
2009		8,791,969,661		9,716,393,321		924,423,660	10.5
TOTAL	\$	32,749,323,558	\$	35,799,925,825	\$	3,050,602,267	9.3 %

Note: Additional 6 Senior Executive titles excluded for Adobe.

Source: Defendants' employee compensation data; Conduct Regression Results.

² Missing job title information prior to 2005.

IV. Dr. Stiroh's Analysis of Defendants' Compensation and the Non-Compete Agreements Contains Errors and Omissions

A. Dr. Stiroh Mischaracterizes the Nature and Significance of Defendants' Non-Compete Agreements

1. Dr. Stiroh Ignores Evidence of the Importance of Cold Calling

4. Dr. Stiroh claims that the amount of competition affected by the Non-Compete Agreements was so small that there could have been no broader effects.

"The amount of information allegedly restricted through DNCC agreements was only one of many potential sources of 'price discovery' information available to employees. The impact of the restrictions on cold-calling would have, at most, reduced information to specific employees about specific opportunities."

"The amount of information that might reasonably have been restricted by DNCC agreements is small. Transfers between firms with DNCC agreements represented only a very small fraction (0.2 percent) of the new hires at Defendant firms even before the Class period. In addition, the percentage of a Defendant's new hires coming from a firm with which it had a DNCC agreement did not substantially decrease during the Class period. As overall hiring did not decrease during the Class period, and the percent of new hires between companies with a DNCC agreement was small before, during and after the Class period, there is no basis to assume that the amount of 'price discovery' information was lessened during the Class period."

5. The theory of information suppression that I have put forward together with internal equity considerations allows for the possibility that wages were

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⁵ Stiroh Report, par. 7.c.

⁶ Stiroh Report, par. 7.d.

suppressed throughout the Class even though non-equivalent channels of information were still open. There is not any basis for Dr. Stiroh's assertion that the information available to a firm's employees would not be materially diminished by a reduction of cold calling from what Dr. Stiroh characterizes as "one, two, or three firms that together make up a tiny fraction of potential hiring demand for those employees." Dr. Stiroh lacks support for the claims she makes about the availability of alternative equivalent sources of information. As described in my earlier reports, cold-calling played a unique role in conveying information about market compensation opportunities.⁸

- 6. There is no basis to assume that new hires act as a substitute for the information conveyed by cold-calling, or that the number of new hires from one defendant to another can be used to measure the information lost when they decided to stop cold calls.
- 7. Even in the narrower realm of movement, there's a qualitative difference between information conveyed when passive candidates are successfully poached and that from normal arrivals and normal departures. The successful recruiting of a new employee who is appropriately slotted into the firm hierarchy does not reveal better jobs elsewhere the opposite is the case. Also many normal departures occur with the tacit agreement of the firm, and do not necessarily suggest to other workers the existence of better jobs elsewhere.
- 8. The agreements did not ban individuals from leaving one Defendant to join another Defendant--rather they banned the active solicitation or competitive bidding to attract them.⁹ The fact that some individuals did transfer between Defendants by itself tells us nothing about the number who would have been interested in transferring had they received a cold call prevented by the agreements. This interest could have been met with a counteroffer that convinced the affected employee not to leave, a normal reality that means it

⁷ Stiroh Report, par. 89.

⁸ See e.g., Leamer Report, pp. 33-35.

⁹ Leamer Report, par. 23.

does not take movement of workers for cold calling to have an impact on wages. It also tells us nothing about the competitive pressure that would have been put on Defendants' pay systems by the additional cold calls in the absence of the agreements. Mobility is not the same as movement. There can be mobility without movement and movement without mobility.

2. Dr. Stiroh's "Bilateral Conspiracy" Theory Ignores the Over-Arching Character of the Alleged Conspiracy

- 9. Dr. Stiroh claims that the conduct variable I used does not account for the extent to which the flow of information about job opportunities was suppressed by the agreements (which is the primary medium through which Plaintiffs allege the agreements impacted compensation). In her opinion, because the conduct variable is binary, it does not reflect the bilateral nature of the agreements and does not allow a firm that has an agreement with a larger firm, rapidly growing firms or multiple firms to experience greater impact.
- 10. For the reasons I have previously explained, and with which Dr. Stiroh appears to agree, it is not possible to "disaggregate" the regression at the level she would like. However, were this view of the Non-Compete Agreements as a collection of bilateral agreements to be accepted, an imperfect--but implementable--alternative would be to assume that the effect of the Agreements is proportional to the mobility foreclosed. The sensitivity of the regression to this issue can be tested using the number of employees in Defendants with whom a Defendant had an Agreement (reported below). The results although different are in line with the damages calculated by the correct regression, demonstrating that the regression is not sensitive to this issue.¹¹ However, this is still not the correct regression as it imposes a specific assumption about impact of the Non-Compete Agreements on mobility (which is impossible to observe).

¹¹ Note that this is not the same as disaggregating the model by Defendant, as Dr. Murphy and Dr. Stiroh have each put forward among their various analyses. As I described in my earlier Class Cert Reply Report and discuss below, disaggregating by employer, the way Dr. Murphy and Dr. Stiroh have, is not appropriate.

¹⁰ Stiroh Report, par. 182.

3. Dr. Stiroh's Change in Intel's Agreement Date is Inconsistent with Plaintiffs' Allegations and Documents

- 11. Dr. Stiroh suggests calculating damages based on the assumption that the start date for Intel's participation should be 2006 rather than 2005. This change is not consistent with factual evidence about Intel's participation in the Non-Compete Agreements and is therefore not worth exploring.
- 12. Numerous Google documents, one of which Dr. Stiroh reviewed, explicitly include Intel on the list of companies that "have special agreements with Google and are part of the 'Do Not Call' list" under the stated effective date of March 6, 2005.¹³ A statistician has a duty not to ignore basic facts in conducting regressions. Dr. Stiroh apparently ignored this document.

B. Dr. Stiroh Incorrectly Downplays the Common Elements of Defendants' Compensation; Dr. Becker Makes Similar Errors

- 13. Drs. Stiroh and Becker wave the flag of individual compensation variability that we have seen many times before. As I have explained before, internal equity requires a semi-rigid compensation structure, such as the Defendants had, not identical outcomes for every employee in every job title. In other words, the presence of individual effects on compensation by no means rules out the predominantly common effects that I have detected. Dr. Stiroh also introduces the new idea that detecting an effect should depend on seeing a "pattern" in average trends in the data. However, there is no support for this proposition in her report or in economic theory.
- 14. As I described previously, consistent with the economic frameworks,

 Defendants utilized pay ranges in setting compensation. 14 Dr. Becker
 mischaracterizes the extent of variation in class employees' salaries as evidence
 of lack of salary structure. 15 She focuses on the range of salary outcomes

¹³ See GOOG-HIGH TECH-00008283.

¹² Stiroh Report, par. 10, 179.

¹⁴ See Leamer Report, pp. 49-52 and Leamer Rebuttal Supplemental Report, pp. 33-37.

¹⁵ See e.g., Becker Report par. 21 and 99.

observed in the defendants' job grades or job titles and merely by providing examples of seemingly wide ranges, ¹⁶ she makes sweeping conclusions about there being no apparent structure. ¹⁷ I note that Dr. Becker has provided no correlation or regression analysis ¹⁸ to investigate the extent of variation that is explained by factors that typically determine compensation (factors such as experience, tenure, age, education etc).

15. I addressed this issue in detail under the common factors (hedonic) analysis presented in the Leamer Report and the Leamer Reply Report. The common factors analysis showed that most of the variation in individual compensation is explained by factors such as age, company tenure, gender and title. ¹⁹ As I explained:

"[] the Defendants have focused on the variability in the compensation received by Class Members. This discussion misses the mark. Even in firms with a 'somewhat' rigid salary structure, it is to be expected that there will be salary variations for people sharing a title. This is not a symptom of firms setting compensation randomly but almost certainly reflects differences in the people and jobs that are part of the compensation structure."²⁰

16. As I have also described in my prior work, and consistent with economic principles and Defendants' practices, there was a high degree of correlation over time, at the job title level, among the compensation levels of Defendants' employees.

Becker Deposition, December 10, 2013, 177:18-183:10;. 31-32.

¹⁶ Becker Report par. 52-54, 65-67, 73-75, 87, 89, 92-93, and 97.

¹⁷ Becker Report par. 34, 37.

¹⁹ Leamer Report pp. 53-61 and Leamer Reply Report par. 61-66.

²⁰ Leamer Reply Report par. 61.

- 17. In my Supplemental Report and Rebuttal Supplemental Report, I presented a study of correlation of title compensation with average compensation for the rest of the Technical class, in both levels and rates of change. These contemporaneous correlations understate the extent of the common compensation structures since they do not capture the full dynamic relationship between Class members' compensation (for example they do not reflect the lagged effect that works to bring compensation back into line, an effect that I also analyzed previously). Figure 1, reproduced from the Leamer Rebuttal Supplemental Report, depicts some of the commonality in the Defendants' payroll data.²¹ It shows the distribution across titles of correlations between the growth of Defendants' title average real compensation and the growth of real reference compensation.²²
- While the correlations between the levels of these variables can be influenced by 18. common upward trends, the correlations among rates of growth are free of common trend effects and focus attention on the co-movements year by year. The top histogram of Figure 1 leans heavily towards the right in favor of high correlations. The mean correlation is 0.61 and the standard error of this population of correlations is 0.37, which indicates a high degree of contemporaneous co-movement of compensation among most of the Technical Class titles of each defendant. The bottom histogram, which shows the distribution weighted by employee years, much more substantially leans to the right. Weighted by Class period employee years, the mean correlation is 0.82. In addition to demonstrating that most workers were in titles that had a strong association with the firm overall, this figure reconfirms a point I made previously²³ that the averaging across individuals, by filtering out individual idiosyncrasies, helps to reveal the common effects when the number of individuals is large. This filtering works best when there are many employees in

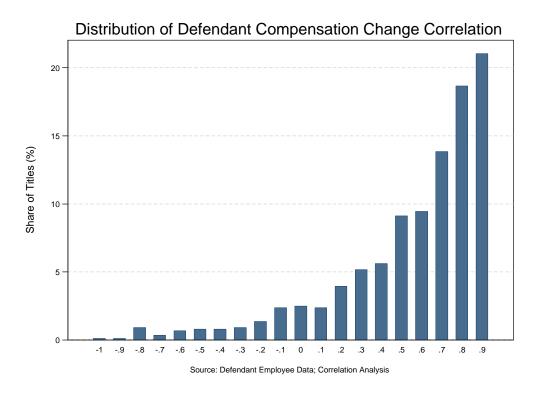
²¹ Leamer Rebuttal Supplemental Report, Figure 4.

²² Reference Compensation is defined as average compensation across remaining titles.

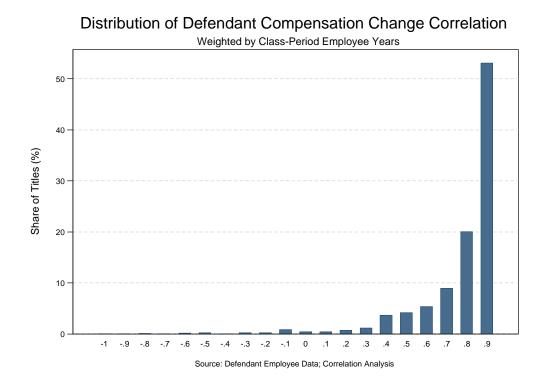
²³ E.g., Leamer Rebuttal Supplemental Report, par. 19, Leamer Supplemental Report, pp. 2-3, 12-13.

- a title, as infrequently populated titles are expected to have lower correlations with the firm overall purely for statistical reasons.
- 19. Having said that, there is no reason to suspect that people among sparsely populated titles will somehow be treated differently and not be part of firmwide sharing. Dr. Becker makes reference to the large numbers of job codes and titles at Adobe and Lucasfilm that had very few people in them.²⁴ She cites the fact 19% of the Adobe job codes in 2005 had one class member. Similarly, she notes that 56 of the 103 Lucasfilm job titles in 2007 had only one class member. These facts do not imply that these individuals will be isolated. For instance, I find that base salaries of employees belonging to one-employee job codes (or titles) are highly correlated base salaries of other employees (0.85 for Lucasfilm, 0.82 for Adobe).

Figure 1: Correlations of Annual Growth of Defendant Real Title Compensation with Real Reference Compensation Growth



²⁴ Becker Report par. 72, 97.



a. There is No Basis to Consider this Degree of Correlation 'Low'

- 20. The results of the correlation analysis I conducted are consistent with a somewhat rigid compensation structure.²⁵ Defendants complain the correlations are not high enough. However, variables do not even need to be highly correlated to reflect important causal relationships, and Dr. Stiroh cites no threshold or level that these correlations have failed to meet.
- 21. Even variables recognized by Dr. Stiroh as important do not track closely with compensation. For example, correlation coefficient of age total compensation in 2008 is 0.15. The low number may come as a surprise considering that one would expect age to have important influences on compensation. This is highly pertinent example of data which at the individual level almost completely mask an important effect, while this effect is quite apparent when data are averaged over individuals, or when a regression analysis is used to extract the common effect. The magnitude of correlation coefficients should be interpreted with

²⁵ See Leamer Supplemental Report, par. 24.

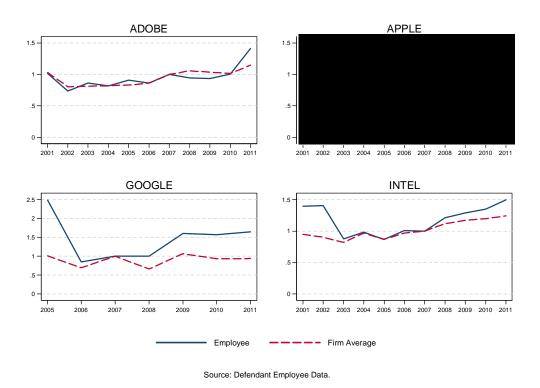
- care and with regard to the context. There can be important underlying economic relationships even when the correlation may seem low. That is why regression analysis is used--to capture complex multivariate relationships.
- 22. As noted above, the typical correlation (weighted by title employee-years) between title compensation changes and compensation changes of other Class titles was 0.82. Dr. Stiroh uses a lower number from Dr. Murphy that does not reflect the volume of data for each title. She apparently never verified or analyzed his work. In doing so, she over-represents the effect of rarely used titles where the lack of data means the common component of compensation is more difficult to detect.
- 23. In support of her claim that there are no compensation structures within the firm, Dr. Stiroh presents illustrations of total compensation for four different pairs of employees with about 0.6 compensation correlation.²⁶ These illustrations are not representative and only reveal why I have not relied on correlations of levels alone and have also produced correlations of changes as well as multivariate regression analysis. Correlations of levels can suffer from what I call a "two-trends" problem in which the correlations are influenced by the common trend. The series are misleading because 1) the 0.6 figure was the change correlation--not the level correlations reflected in the charts, 2) 0.6 is lower than typical change correlation in the analysis I conducted, and 3) the analysis I conducted was of the title structure—the relationship between title compensation and firm total average compensation. Dr. Stiroh's charts compare individuals of different titles with their own career paths. In such a chart the individual elements of compensation will obscure the common elements.
- 24. Dr. Stiroh pointed out that title and firm were the most important determinants of compensation in my common factors analysis. The relevant question is whether there is evidence that titles are not tied together sufficiently tightly such that impact is shared across the class. Employees with titles that did not move with the rest of the firm were rare (and when there are fewer employees in a

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²⁶ Stiroh Report, par. 128 and Exhibits IV.17,18, 19, and 20.

titles the common elements of compensation are less visible). As can be seen in the figure above, less than 20 percent of Class employee years were in a title with its correlation at or below the 0.6 level used in the examples highlighted by Dr. Stiroh. To show what images look like of a typical change correlation I present below charts comparing average real total compensation of four firms with total real compensation of an individual employee when the change correlations are 0.70. The figures, while not tracking exactly, do track together.

Figure 2: Examples of Compensation Correlation 0.7



- b. My Sharing Regression Results Confirmed the Existence of a Compensation Structure that Strongly Supported Internal Equity
- 25. Level correlations and change correlations do not provide a complete picture of relationships and cannot control common external effects. Thus I conducted a regression analysis of the dynamic relationships including internal equity within the Defendants' compensation systems. Regression analysis is able to control for common factors and to capture more complex dynamic relationships than correlation analysis.

- 26. As I reported in my Supplemental Report and Rebuttal Supplemental Report, the sharing analysis shows that even controlling for external factors there was contemporaneous sharing within the firms and a corrective lagged effect which acted to bring individual compensation more in line with the compensation structure.²⁷
- 27. Dr. Stiroh claims, without elaboration, that "changes in the mix of employees within each job title" make this work "meaningless." However, her "analysis" (her Exhibits IV.15 and IV.21-24) only shows that these changes in composition occur; she does not explain how this in any way undermines my own analysis or conclusions. Indeed, the noise introduced into the correlations by changes in composition simply reinforces the finding that there is rigidity in the title-level pay structures employed by the Defendants.
 - c. Wage Disparity is Lower Within Comparable Groups of Employees
- 28. Dr. Becker similarly says that there were wide ranges for salaries within title grades at the Defendants and suggests that this contradicts the semi-rigid salary structure and sharing relationships I have described.²⁹ This is like saying that at any given age (or tenure) there were wide ranges of salaries and therefore age (or tenure) does not affect compensation, which we know is not the case. I have established with both cross-section and time series analyses that compensation at these firms have associations that reveal a semi-rigid salary structure not one in which every individual received the same increase but one in which there were important and detectable commonalities.³⁰
- 29. The common factors analysis showed that the vast majority of compensation differences are related to common factors such as firm, title, age, etc. Other common facts exist and were commonly known to employees and their firms, but were not provided in the data (e.g., education, past experience, job

²⁷ See e.g., Leamer Supplemental Report, par. 24-29.

²⁸ Stiroh Report, par. 132.

²⁹ Becker Report, par 34-37, 52-56, 65-68, 73-75, 86-87, 89, 92-93, 97.

³⁰ See Leamer Supplemental Report and Leamer Rebuttal Supplement Report.

assignment, performance, skills). These other common factors would have been part of the firms' compensation structures. Because these data were not available, the amount of compensation variation attributable to the firms' compensation structures is even larger than what I was able to estimate.

30. Dr. Becker presents a set of examples of the wide variation in salaries but fails to control for differences in employee and job characteristics, as I did. In her discussion regarding wage disparity, Dr. Becker ignores all employee characteristics when citing the "wide" ranges for salaries and grades. In doing so, she lumps all employees together based on titles or grades to infer that these wide ranges could not plausibly be evidence of a salary structure. However, by taking into account very basic common employee characteristics (such as tenure, age, location, and gender), much narrower ranges begin to reveal themselves.

	These ranges are calculated by lumping all employee
salary grad	de together regardless of location, age, tenure, and other characte
that direct	tly explain most of the variation in compensation. In the case of t
title, locat	ions span Silicon Valley, California's Central Valley, Oregon, and
Arizona, a	and many other locations. Likewise, tenure for these employees ca
range from	m 1 to 31 years and age from 25 to 66. Once these factors are
controlled	l for, salary ranges begin to shrink.

32. I provide further counter-examples to Dr. Becker's quoted salary ranges in Appendix A.

³¹ Becker Report, par. 52-54.

C. A Compensation Trend is Irrelevant to Whether Class Members Were Undercompensated

"There is substantial volatility in average total compensation, average base salary, average bonus and average equity, and there does not appear to be any consistent pattern of changes to compensation practices at these firms concurrent with the timing of the DNCC agreements."³²

- 33. Dr. Stiroh observes that there was an overall increase in average total compensation between 2001 and 2011 and that she does not see an "easily observable" pattern in changes to compensation trends during the Class Period. Visible trends are irrelevant to the question at hand: were Class members undercompensated? My work, which has explicitly controlled for the trends, has answered this question affirmatively. Dr. Stiroh implies one should expect to see a visible sharp drop in the compensation series coincident with the start of the agreements. However, the fact that compensation rose does not imply there was no undercompensation. The question is how much *more* would it have risen if the agreements were not in place. That is why it is necessary to run a regression analysis that controls for the influence of various different factors and that can compute the 'but-for' compensation.
- 34. My damages regression includes a number of variables that can account for the upward trend in compensation, including the lagged compensation variables, firm performance variables, market variables, and a trend variable. In other words, compensation trend is a non-issue except for the correlations of levels of compensation. That is exactly the reason why I reported correlations among changes in compensation to go along with the correlations among levels.
- 35. There is no significance to Dr. Stiroh's claim that the period 2005-2009 does not look different.³⁴ There is no support in economic theory for the proposition

³³ E.g. Stiroh Rough Deposition, December 9, 2013, 95:11-96:2; Stiroh Report, pp. 30-32.

³² Stiroh Report, par. 7.b.

³⁴ E.g., Stiroh Report, pp. 30-32.

that prices must go up during a price fixing conspiracy, or down during a wage suppression conspiracy. Sometimes prices will go down and wages will go up for reasons beyond the control of the cartel, and the cartel succeeds simply by mitigating the effects of those forces. Looking for a "pattern" in the simple movement of levels over time has no relevance to the task at hand and, indeed, is designed to mislead.

36. The question is what compensation would have looked like but for the alleged Non-Compete Agreements (and this is not observable) relative to actual compensation. Although the but-for compensation I found with my model implies that Defendants undercompensated their employees, but-for compensation does not "look different" during the Alleged Non-Compete Agreements relative to before or after the Non-Compete Agreements. Nor would it be expected to.

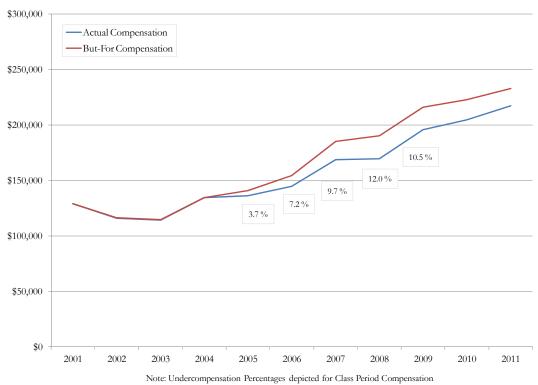


Figure 3: But-For Compensation

37. On the other hand, hiring does look different before the Alleged Non-Compete Agreements from when they were adopted by the larger five Defendants.

- Hiring by Defendants ticked up sharply in 2005. Between 2005 and 2009 the Defendants workforces grew by more than 10 percent.
- 38. The Non-Compete Agreements were put in place when the tech job market was starting a much delayed recovery after the tech bust of 2001. For that reason, absent the agreements, we should be expecting more recruiting activity in 2005-2007, prior to the economic downturn that began in 2008. The continued hiring by Defendants of employees from firms with which they had DNCC agreements does not show that but-for the agreements there would not have been even more hiring, and, moreover, the hiring rates are a very imperfect measure of the information associated with cold calling because firms have the option to respond to a cold call with higher compensation which can persuade a valued employee to stay, not go. It is mobility not movement that firms must deal with.

Number of New Hires / Previous Year's Employment (Percent)

10

5

2001 2003 2005 2007 2009 2011

Source: Defendant Employee Data

Figure 4: Defendant Hiring Rate

Figure 5
Size of Technical Class

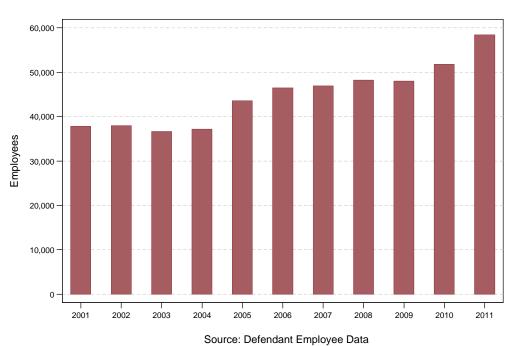


Table 3: Growth in Class Headcount (2005-2009)

	Number of l	mployees		
Employer	2005	2009		
	(1)	(2)		
ADOBE	2,326	2,794		
APPLE	3,925	5,921		
GOOGLE	2,306	7,199		
INTUIT	2,068	2,547		
LUCASFILM	139	387		
PIXAR	505	741		
Total	43,610	48,038		

Source: Defendant Employee Data.

D. Contra Dr. Stiroh, Promotions and Changes in the Mix of Employees Do Not Undermine My Analysis of Common Impact

"Employees can be promoted to different job titles and earn salary increases commensurate with their promotion. This routine and expected event in an employee's career is completely unaccounted for in Dr. Leamer's analysis." 35

"These differences [dispersion in pay changes] can be caused either by movement across job titles changing the mix of employees being averaged together or by disparate compensation changes within the job title. Both of these reasons are inconsistent with Dr. Leamer's contention that the allegedly rigid compensation structure and internal equity concerns will lead to widespread salary suppression caused by a significant ripple effect." 36

- 39. Dr. Stiroh appears to misunderstand the question being asked. Having shown that job title explains most of an employee's compensation, I next asked whether a structure exists at the title level binding together compensation within the firm. The fact that Defendants sometimes rewarded a worker with more compensation by promoting them to a new title does not *contradict* this structure; it *confirms* it, for the simple reason that if the structure didn't exist all such employees could be fully rewarded without promotions. The title-based compensation structure at each firm, in turn, means that the reactive and preemptive actions that would have been sparked by more cold-calling would have been broadly felt across the firm.
- 40. The error of this view can be further illustrated by two examples I discuss below.

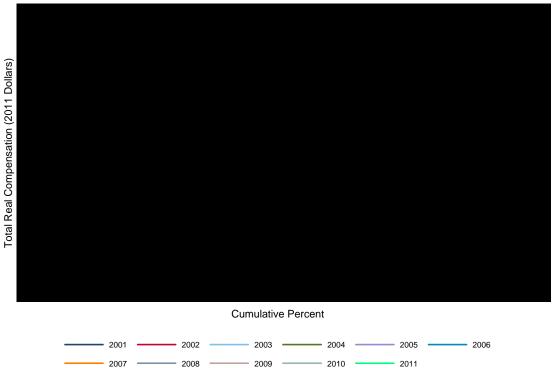
³⁶ Stiroh Report, par. 124.

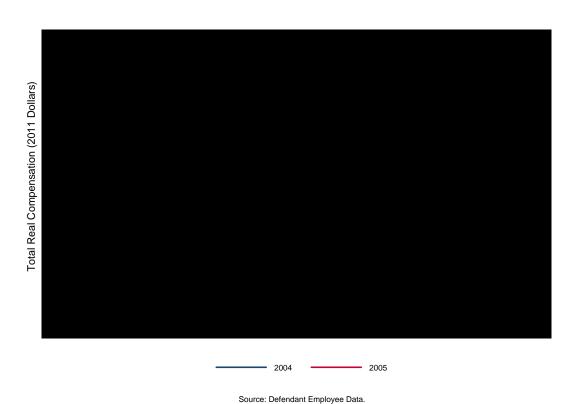
³⁵ Stiroh Report, pp. 44-47.

This is Illustrated by the Macromedia Acquisition, Which Did Not Appear to Disrupt the Salary Structure

41. One example of the structure in action can be found in the acquisition of Macromedia by Adobe, which Dr. Lewin also comments on. The acquisition was finalized December 3, 2005, and first showed up in the payroll data in 2005. The figure below illustrates the cumulative distribution of total real compensation for Adobe employees in each year in the sample. The year 2005 does not stand out and it appears thus the Macromedia employees seem to have been folded into the Adobe salary structure without much affecting the distribution of earnings. The next figure includes only the 2004 and 2005 data to see if the Macromedia acquisition had a noticeable impact at least in 2005. There is very little difference between these cumulative distributions, and the basic salary structure at Adobe was not disturbed by the Macromedia acquisition.

Figure 6: Adobe Total Real Compensation Distribution by Year





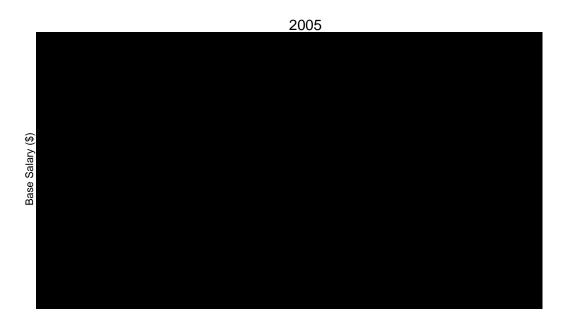
42. I have argued that new employees need to be slotted in the existing job structure to prevent outbreaks of complaints about internal equity. For Adobe titles used for 5 or more employees, I examined whether the acquired employees from Macromedia were placed within the existing salary structure. Figure 7 shows the base salaries of the acquired Macromedia employees in comparison to pre-existing salaries on the titles they joined in 2005 and the following year.³⁷

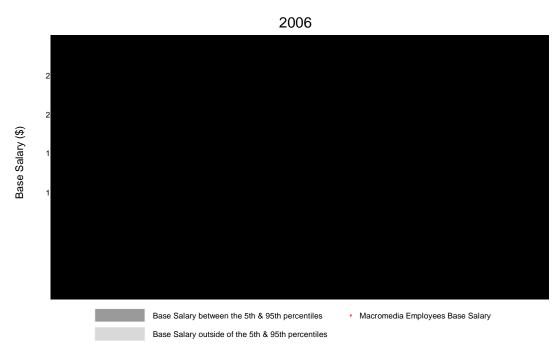
Thus the acquisition was largely consistent with the existing salary structure and salaries came more into line over time,

consistent with my sharing analysis.

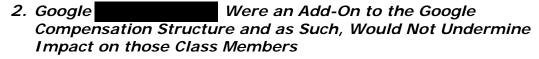
³⁷ Titles having at least 10 Adobe employees and at least 5 Macromedia employees in 2005 are shown and the same set of titles is tracked in 2006. The figures on top of the bars represent the number of employees acquired by Macromedia followed by the number of existing Adobe employees sharing the same title in parentheses in that year.

Figure 7: Base Salaries of Macromedia Employees and Existing Salary Structure





Source: Defendant Employee Data.



- 43. Another example raised by Dr. Stiroh is the

 Stiroh claims that the damages model I presented fails to account for certain

 employees. However, Dr. Stiroh admitted at deposition that her complaint in this regard is simply an extension of her overall attack on my work and contains no new or distinctive analysis with respect to these individuals.³⁸
- 44. And indeed it is. As I have repeatedly explained, the existence of individual differences does not mean that the individuals do not share common effects including the firm's success and also internal equity effects.³⁹

 While Dr. Stiroh emphasizes the different outcomes for these workers within the structure, she never says or even suggests that they are outside the structure itself. Furthermore just because these highly valuable employees benefited from a pre-emptive strike against competition does not undermine the conclusion that the strike would have been even greater had competition for their services been stronger, as it would have absent the DNCC agreements.
- 45. For these same reasons, I disagree with Dr. Becker's opinion that the fact that there is variation in the extent of equity compensation across groups of employees, implies that the sharing effects of equity grants will not extend beyond these sub-groups.⁴⁰
- 46. The figures below show three percentiles of the distribution of the ratio of salary supplements to base salary for Google employees in each year; the median, the top 10th percentile and the top 1 percentile. The figure at the top has a logarithmic vertical scale to facilitate comparisons. The median and the top 10% in this figure have an obvious association with each other, moving up

³⁸ Stiroh Rough Deposition, p. 303:18-305:4.

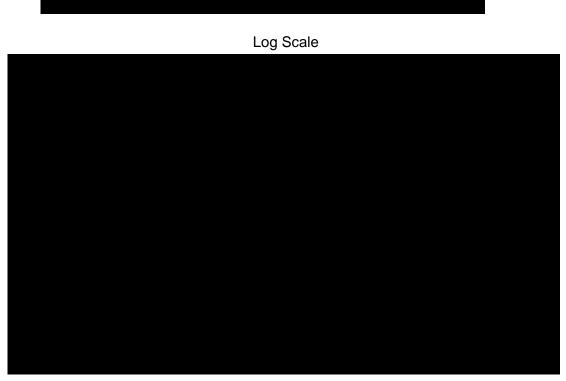
³⁹ For example, stock prices vary substantially, yet an interest rate announcement by the Federal reserve is capable of influencing them in a common, broad-reaching fashion.

⁴⁰ Becker Report par. 122.

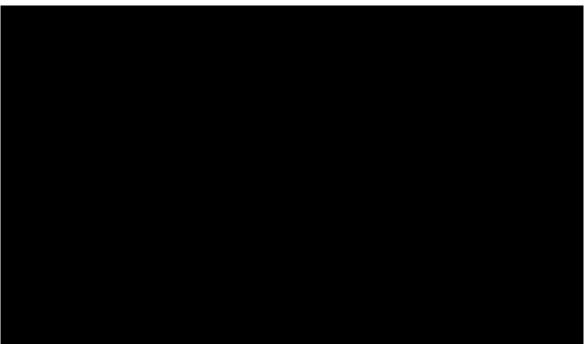
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December 11, 2013

and down together with greater swings for the more compensated employees – the top 10%. While as Dr. Stiroh suggests, the top 1% in 2007 had much larger supplements (in excess of 16 times base salaries), the direction of movement was the same as experienced by the 50% and the 90%.



Source: Defendant Employee Data



Source: Defendant Employee Data

47. employees were subject to the same impacts of other employees given that their additional compensation was an add-on to their other compensation, which was part of Google's compensation structure.

V. Dr. Stiroh's Criticisms of My Damages Analysis are Incorrect or Irrelevant

A. Dr. Stiroh is Incorrect to Claim that My Conduct Variable is Poorly-Suited to the Analysis

"The 'conduct' variable Dr. Leamer uses does not support his theory of harm, nor does it accurately measure the alleged information loss as a result of the agreements at issue. In fact, it is inaccurate for Dr. Leamer to call it a 'conduct' variable. It is simply a time indicator that captures all changes in compensation that have not otherwise been accounted for during the alleged Class period. As a result, there is no basis to assume that the effect that Dr. Leamer appears to be measuring arises from a reduction in information flow as opposed to other microeconomic and macroeconomic factors that occurred concurrent with the Class period but are omitted from his damage analysis."⁴¹

- 48. This paragraph leads me to believe that Dr. Stiroh has fundamentally misunderstood my work. The whole purpose of regression analysis is to control for exactly the "factors" to which Dr. Stiroh alludes, but does not mention by name.
- 49. My specification is suited to my assignment: to measure total damages to the Class. It was not designed to measure separate precise damages to each individual Class member on a year by year basis, nor firm total damages on a year by year basis. My advice as a statistician is that, while the goal of disaggregating by firm, year and individual is laudable, it cannot be achieved with the limited data set that we have to rely on, as demonstrated by the wild

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⁴¹ Stiroh Report, par. 7.h.

- results obtained by Dr. Stiroh (and Dr. Murphy before her) when she attempts to do so.⁴²
- 50. As further explained below my analysis has included the most economically relevant variables and has been conducted properly. Dr. Stiroh's criticisms are without basis in true statistical methodology.
- 51. Of course I recognize that my estimated model could change dramatically if another relevant variable was included that mimicked my CONDUCT variable taking on one level before and after the agreements were in place, and taking on a distinctly different level during the agreement period. I have not found such a variable and neither has Dr. Stiroh.

B. Dr. Stiroh's Estimation of the Model with Base Compensation Alone is Improper

- 52. My compensation model is attempting to measure the effect of the conduct on employee's total compensation. To appropriately model an economic variable like *total* compensation it is important that it be accurately measured. Leaving out supplemental compensation creates a meaningless model that neither estimates total undercompensation nor effects on base compensation.
- 53. If Dr. Stiroh wanted to study the Defendants' allocation of compensation between equity, bonuses, and base salaries she would need to look at the factors influencing these decisions. She has not done so and it is not clear that such a model would be practical. What Dr. Stiroh has done is put forward an analysis of incomplete data that sheds no light on Class members' undercompensation.
- 54. Dr. Becker also makes references to the Defendants' use of base vs. equity compensation in her criticism of Dr. Hallock's assertion that base and equity compensation are highly correlated at these firms.⁴³ I studied the correlation between the two forms of compensation across individuals during the class period and find that there is evidence of a positive association (median of the

⁴² See Stiroh Report, par. 181 and Exhibit VI.5; Murphy Report, par. 116 and .Appendix 9A-9B.

⁴³ Becker Report pp. 26-31.

- annual correlation by year and firm is .6). This is an alert to the dangers of viewing either one of these components independently.
- 55. On a related topic, Dr. Becker also wrongly concludes that there is no evidence of equity grants being in line with a salary structure.⁴⁴ Intel and Google provide the opportunity to test this, since they provide numeric job grades that are reflective of a hierarchy. Both the value of equity compensation granted and its share in total compensation, in almost all years, are highly correlated with the job grade level as depicted in Table 4.

Table 4: Equity Compensation rises with Job Grade

		etween Equity and Job Grade	Correlation between Share of Equity Compensation in Total Compensation and Job Grade		
		GOOGLE		GOOGLE	
_	Year	(Grades T1-T9)		(Grades T1-T9)	
		(2))	(4)	
	2001	0.754		0.670	
	2002	0.694		0.655	
	2003	0.812		0.725	
	2004	0.887		0.851	
	2005	0.834		-0.574	
	2006	0.935		0.984	
	2007	0.794		0.970	
	2008	0.895		0.758	
	2009	0.922		0.986	
	2010	0.834		0.940	
	2011	0.909		0.976	

Note: Correlations are measured at job-grade average.

New hires are excluded.

 $Source: Defendant\ Employee\ Data.$

⁴⁴ Becker Report par. 100-102.

C. Dr. Stiroh's Claims that the Model's Results are Inconsistent with Well-Established Economic Relationships are in Error

56. Dr. Stiroh claims that the damages model yields counter-intuitive and implausible results that are inconsistent with Plaintiffs' theory of harm or well-established relationships in labor economics. In her view, it yields the 'wrong' signs for several coefficients that raise doubts about its reliability. As I explain below, this supposed "criticism" demonstrates a serious misunderstanding (or lack of knowledge) by Dr. Stiroh about statistics.

1. The "Wrong" Signs Come from a Collinearity Problem not Model Misspecification

57. Dr. Stiroh has identified what she thinks are wrong signs in the estimated coefficients of my damage model and claims that these wrong signs are evidence of a misspecified and unreliable model.⁴⁵ This is a mistaken opinion and a surprising one since in at least two of my three depositions I explained why it is very difficult to know what the "right" signs are in a multiple regression and why the signs of the coefficients in my damage model are not symptoms of an unreliable model.⁴⁶

58. Dr. Stiroh says:

"A well-known effect of misspecification and omitted variables in regression analyses is that coefficients can be estimated with the 'wrong' sign. This seems to be the case with Dr. Leamer's analysis. Dr. Leamer's regression produces unexpected results with respect to the effect of age and other variables on compensation. The results of his regression show a negative coefficient with respect to age, and a positive coefficient with respect to age-squared. This is contrary to the expected signs based on economic literature on wage modeling. The implication of Dr. Leamer's result is that the older a person is, the less they are expected to be paid, all else equal. This

⁴⁶ Leamer Deposition, October 26, 2012, 119:12-120-17.

⁴⁵ Stiroh Report, par. 161-165.

effect reverses at age 63, at which point the impact of age on an employee's compensation becomes less negative as age increases."⁴⁷

59. Dr. Stiroh raises similar issues about other coefficients, and then she concludes:

"Because Dr. Leamer's model produces counter-intuitive results and Dr. Leamer has not provided an explanation for why the unusual results are reasonable in this market setting, one can have no confidence that the impact and damages he estimates from the model are reliable."⁴⁸

- 60. As a matter of fact I did provide a rather complete explanation for what Dr. Stiroh considers "wrong" signs in my most recent deposition, enough that a competent expert should understand. I quote from that deposition below and put items in bold that should have been an adequate explanation for Dr. Stiroh.
 - Q. So you would agree with me that this shows a negative coefficient which in your model would mean that two employees at the same defendant with the same tenure, everything else in the model being equal, the model estimates that the older worker would be paid less; correct?
 - Q. BY MR. RILEY: Why is that not correct?
 - A. Well, if you said -- if you formed the predicted compensation using this model and then you looked at the age compensation distribution, it's going to very closely reproduce the sample. And the reason that this is confusing -- believe me, I was worried about this, too. And you need to know that this is very dependent on the lag structure that we have here.

⁴⁷ Stiroh Report, par. 161.

⁴⁸ Stiroh Report, par. 165.

So the age is going to be to some extent picked up by how much you earned the previous year. Age is going to be picked up to some extent how much you earned by the year before that. So age is entering into this calculation [in a] very complex way through these lag effects as well.

Q. So these variables are interdependent, then?

THE WITNESS: I think the better way of saying it is the interpretation is interdependent. It's a naive interpretation is [] that you suggested, which is that this model would imply that the age earnings profile is upside down. And trust me, the model overall doesn't have that.

The peculiar feature is that that age coefficient has that sign, and it has to do in this case with the dynamical model that's being estimated. We know -- we know that if you didn't have the dynamics in there and you did it year by year, you'd get that upward sloping profile that you'd expect.

Q. In fact, the log of age squared has a positive sign, whereas in your analysis of common factors, it has negative sign?

A. I [tried] to explain that. Shall I explain it [again]? The common factor is estimated -- regression is estimated year by year. There are no lagged impacts. You're just looking at the structure of wages in a particular year. It's a cross-section. It's a snapshot.

This is a dynamic model. And the data set that's used to estimate the dynamic model is exactly the same data set that was used for those snapshots. So this model that you see in front of you embodies that curve of compensation, the exact same curve. It's just that it's

embodied in a way which is pretty hard to pick up in a sense that these coefficients turn out to be the opposite of what they were in the previous exhibit that you showed me.

Q. And that caused you concern that the coefficients here were the opposite of what they were in your conduct, your common factor analysis; correct?

THE WITNESS: It attracted my attention, yes.

Q. BY MR. RILEY: And did you perform any analysis on that to understand why they are opposite from what one would expect?

A. Well, I worried about it, and as I already indicated, that it depends on the lag structure. So if you choose a different lag structure, this variable's 5 to 18. If you eliminate those variables, you're going to reproduce the same shape that you had in the previous equation. That's for sure.

You can get away with the one lag, but if you add the two lag, these things are interacting in a way that makes it hard to interpret the coefficients the way you want to interpret it.⁴⁹

61. Even with the benefit of that testimony, Dr. Stiroh doesn't seem to realize that there are *two* reasons why signs of estimated coefficients may be "wrong:" (1) a misspecified model and (2) collinearity among the variables. A collinearity problem is caused by multiple correlated variables *in the model* competing to explain the same feature of the data, while a misspecification problem is caused by important variables that are *not in the model*. I was clear in my depositions that here we have a collinearity effect, not a misspecification problem.

⁴⁹ Leamer Deposition, November 18, 2013, 939:15-942:10.

62. The potential misspecification problem to which Dr. Stiroh alludes is strictly hypothetical and applies to every regression ever estimated – there might be important variables that are left out. When wrong signs lead an analyst to worry about misspecification, that should precipitate a search for the left-out variables that are causing the problem – in other words, the ones that can be added to the model to "correct" the "wrong" signs. I have made a very serious effort first to identify the categories of variables that should be included in the model and second to identify variables in each category. Rather than offering something constructive, Dr. Stiroh has offered the casual destructive opinion that she suspects there might be important left-out variables because of coefficients in my model that in her "expert" opinion have the "wrong" sign.

2. A Complete Explanation of the Age Coefficients: Why They Have the "Right" Signs, Not the "Wrong" Signs

63. I explained in my deposition (quoted above) that the unusual signs of the age coefficient were a consequence of collinearity between age and the lagged total compensation variables, not a problem with the model. This point can be made completely clear by a study of the Apple data in 2004. Figure 9 is a scatter diagram comparing the age of each Apple technical class employee with their total compensation in 2004. The curve in the midst of this scatter reflects the estimated quadratic equation reported in Table 5. This curve has the expected upward sloping shape of the age-earnings profile with maximum total compensation around 50 years of age, and the coefficients in the corresponding regression reported in Table 5 have the signs that Dr. Stiroh expects. But these signs reverse when a lagged total compensation variable is added to the regression reported in Table 2. Explained in terms of the collinearity point, the lagged total compensation variable is correlated with the age variables and these two variables compete against each other to explain total compensation. Thus collinearity, not a misspecified model is what has caused the "wrong" signs.

Figure 9: Total Compensation vs. Age (Apple, 2004)



Source: Defendant Employee Data Total compensation is adjusted for inflation and expressed in 2011 dollars

Figure 10: Total Compensation Compared with Previous Year vs. Age (Apple, 2004)



Source: Defendant Employee Data Total compensation is adjusted for inflation and expressed in 2011 dollars

Figure 11: Total Compensation Compared with Two Previous Years vs. Age (Apple 2004)



Source: Defendant Employee Data
Total compensation is adjusted for inflation and expressed in 2011 dollars

Table 5: Regression Explaining Total Compensation as a Function of Age and Lagged Total Compensation, Apple Technical Class Employees, 2004

Observation: Employee ID in December of each year **Dependant Variable:** Log(Total Annual Compensation/CPI)

	Model 1		Model 2		Model 3		Model 4	
Variable	Estimate	T-Value	Estimate	T-Value	Estimate	T-Value	Estimate	T-Value
	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
Log(Age)	8.404***	10.009	-0.516	-1.553	-0.516	-1.590	-0.938***	-2.715
Log(Age)^2	-1.072***	-9.234	0.058	1.282	0.058	1.309	0.112**	2.381
Log(Total Annual Compensation/CPI)(-1)			1.029***	137.228			0.803***	48.002
Log(Total Annual Compensation/CPI)(-2)							0.289***	16.527
Constant	-9.949***	-6.572	0.932	1.566	0.932	1.584	1.374**	2.209
Observations	2,942		2,541		2,541		2,231	
R-squared	0.147		0.896		0.023		0.914	

Source: Defendats' employee compensation data.

64. A more illuminating way to understand the "wrong" signs is by noting that the coefficient on the lagged total compensation variable in the regression reported in Model 2 is 1.029, which means that the logarithm of total compensation in

year 2004 is predicted to be 1.029 times the logarithm of total compensation in 2003, thus approximately a increase in total compensation. The age variable in the regression reported in Model 2 is thus not being asked to predict total compensation; it's being asked to predict total compensation minus previous years compensation adjusted upward by ... I venture to guess that Dr. Stiroh doesn't really know what is a right or wrong sign for this regression. It turns out that the younger workers in 2004, who tended to be paid the least in 2003, were the ones who tended to receive the greatest percentage increase in compensation compared with that norm. This is actually what is predicted by the age-earnings profiles – the younger workers get the greatest salary increases. This fact is captured by what Dr. Stiroh has mistakenly called the "wrong" signs in the regression reported in the regression. There is of course nothing wrong about these coefficients – they are just not answering the question that Dr. Stiroh imagines.

- 65. To make sure that there can be no confusion here, I have produced (see Model 3 in Table 5) a regression in which the dependent variable is the logarithm of total compensation in 2004 minus the "predicted" value equal to 1.029 times the log of total compensation in 2003. Please note that the coefficients on the age variables in Models 3 are exactly the same as the coefficients on the age variables in Model 2. Thus my point the age variables in my model are not explaining total compensation; they are explaining increases in compensation compared with a norm.
- 66. The so-called "wrong" signs are even more evident if another lagged total compensation variable is included in the equation as reported in Model 4 in Table 5. In this equation, the predicted log total compensation in 2004 based on previous log compensation is 80% of total compensation in 2003 plus 29% of total compensation in 2002. Compared with this prediction, it is the youngest workers who were doing better, which is clear also in the scatter diagram in Figure 11.
- 67. The signs on the age variable in my model are eminently sensible when the model is fully understood. Thus when it comes to signs of regression

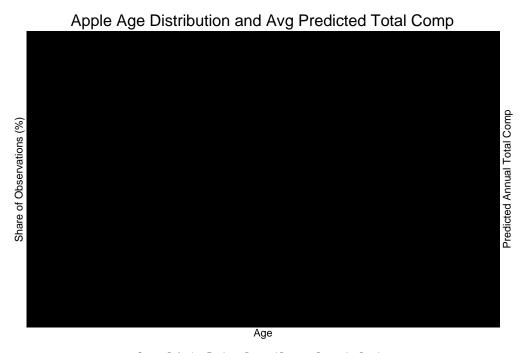
coefficients, Dr. Stiroh has demonstrated that she cannot tell "right" from "wrong."

3. My Damage Model Captures the Normal Age-Earnings Profile

68. I also explained in my deposition that my damage model captures the normal age-earnings profile even though the coefficients on age are the "wrong" sign. 50 To confirm this, I produce in Figure 12 the image of the predicted age-earnings profile implied by my damage model for Apple technical class employees in each year of the sample. The bars in this figure represent the fractions of technical class employees in each of the five-year age intervals and the line is the predicted total compensation from my model averaged over the employees at each age. This line gets a bit "wobbly" at the upper age levels where the number of employees is small and averaging has not eliminated the individual variability that enters into the prediction via the lagged total compensation variables. Except for this wobbliness the age earnings profile of predicted compensation is just what I said it would be.

⁵⁰ "A. Well, if you said -- if you formed the predicted compensation using this model and then you looked at the age compensation distribution, it's going to very closely reproduce the sample." Learner Deposition, 939:24-940:2.

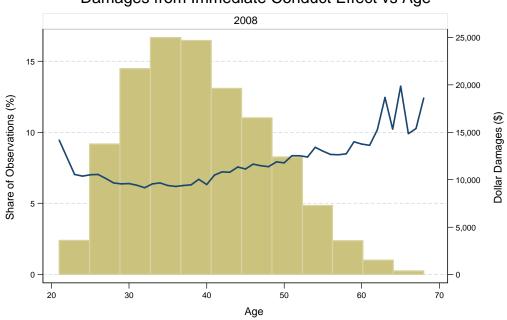
Figure 12



Source: Defendant Employee Data and Damages Regression Results Predicted compensation, expressed in 2011 dollars, is plotted as the blue line on the right axis.

Figure 13

Damages from Immediate Conduct Effect vs Age



Source: Defendant Employee Data and Damages Regression Results Dollar damages are plotted as the blue line on the right axis. Average hiring rate assumed.

69. Additionally, as shown in Figure 13, in dollar terms, damages do generally increase with age.

4. The Damages Increase When the Signs on Age are "Corrected"

70. Finally, to confirm what I said in my deposition "You can get away with the one lag, but if you add the two lag, these things are interacting in a way that makes it hard to interpret the coefficients the way you want to interpret it." I report in Table 6 a regression model that is the same as the one I have presented in my merits report but with only a single lagged total compensation variable. As promised, this yields what Dr. Stiroh thinks are "right" signs for the age variables: positive on log of age and negative on the square of the log of age, both for the age variables not interacted with the CONDUCT variable and also for the age variables interacted with the CONDUCT variable.

⁵¹ Leamer Deposition, 942:7-10.

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Table 6: Alternative Damage Model With Only One Lagged Compensation Variable

Observation:Employee ID record in December of each year Dependant Variable:Log(Total Annual Compensation/CPI)

	Robust		
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3)
			(1)/(2)
1. Conduct * (Log Age - Log(38))	1.2229	0.9872	1.2388
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1635	0.1312	-1.2466
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0474	0.0374	-1.2681
4. Conduct	-0.0873 *	0.0507	-1.7230
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.9121 ***	0.0335	27.2549
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.8637 ***	0.0322	26.8128
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.5315 ***	0.0700	7.5979
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.9140 ***	0.0272	33.5820
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.9006 ***	0.0181	49.7979
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9304 ***	0.0292	31.9028
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6383 ***	0.0884	7.2228
12. Log(Age) (Years)	0.2853	0.3937	0.7246
13. Log(Age)^2	-0.0393	0.0518	-0.7592
14. Log(Company Tenure) (Months)	0.2958 **	0.1335	2.2156
15. Log(Company Tenure)^2	-0.0317 **	0.0149	-2.1317
16. Male	0.0126 ***	0.0042	3.0187
17. DLog(Information Sector Employment in San-Jose)	1.8786 ***	0.6797	2.7641
18. Log(Total Number of Transfers Among Defendants)	0.0691	0.0477	1.4485
19. Year (trend)	-0.0013	0.0111	-0.1216
20. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0235	0.0320	0.7341
21. Log(Total Number of New Hires)	-0.2955 ***	0.0967	-3.0560
22. Log(Firm Revenue Per Employee/CPI) (-1)	0.0052	0.0804	0.0642
23. DLog(Firm Revenue Per Employee/CPI) (-1)	0.0529	0.0751	0.7037
24. APPLE	0.3692	0.3097	1.1921
25. GOOGLE	2.6626 ***	0.4970	5.3575
26. INTEL	-0.0141	0.2696	-0.0523
27. INTUIT	0.0811	0.2436	0.3327
28. LUCASFILM	-0.1322	0.3170	-0.4172
29. PIXAR	1.8016 ***	0.6124	2.9418
30. Location (State) Indicators	YES		
31. Constant	YES		
R-Square	0.800		
Observations	321,854		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

 $Source: Defendants'\ employee\ compensation\ data; St.\ Louis\ Fed\ Reserve; SEC\ Filings$

71. When the model reported in Table 6 is used as a basis for the damage estimate, the damages (reported in Table 8) increase. Although this model with the larger

⁽²⁾ Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.

⁽³⁾ Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.

⁽⁴⁾ Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.

⁽⁵⁾ Observations are restricted to cases in which there was no change in employer in the previous two years.

⁽⁶⁾ Standard Errors adjusted for clustering at employer-year level.

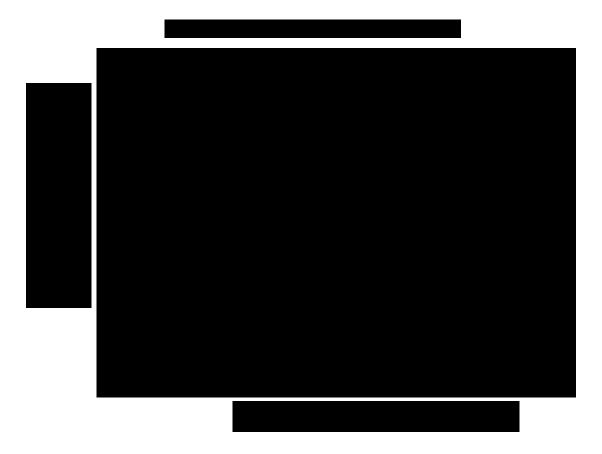
damage number has the "right" signs of the age variables, I have not suggested this model yields the better estimate of total damages because: (1) I am very reluctant for the reasons that should now be clear to impose my guesses or Dr. Stiroh's guesses on the signs of the coefficients, (2) The model with two lagged compensation variables provides the better fit (i.e., the R-squared in my preferred model is higher),⁵² and (3) I have been concerned that the apparent biannual cycle illustrated in the figure below might only be picked up by the lagged compensation. If the variables I have included in the equation (e.g. revenue) do not pick up this cycle, it might be best explained by linking compensation to compensation two years earlier as well as one year earlier. The model with only a single lagged compensation variable reported in Table 6 has a lower coefficient on the lagged Google total compensation, which is the best the model can do to capture the biannual cycle with only a single lag compensation variable. In contrast, in my damage model the sum of Google's to lagged total compensation coefficients is much more in line with the persistence of the other defendants.

Table 7: Estimated Coefficients on First and Second Lag of Compensation

	Mo	Model with One Lag		
Employer	First Lag	Second Lag	Overall	
	(1)	(2)	(3)=(1)+(2)	(4)
ADOBE	0.6738	0.3002	0.9740	0.9121
APPLE	0.7289	0.2456	0.9744	0.8637
GOOGLE	0.4329	0.3687	0.8015	0.5315
INTEL	0.6818	0.2841	0.9659	0.9140
INTUIT	0.6527	0.3045	0.9573	0.9006
LUCASFILM	0.9327	0.0432	0.9759	0.9304
PIXAR	0.6739	0.0941	0.7680	0.6383

Source: Damages Regression Results

⁵² Note that the number of observations has been reduced when the second lagged compensation variable is included because it requires an extra year of data to "get started."



5. Dr. Stiroh Makes the Mistaken Complaint About the Signs of Other Coefficients

72. It isn't just the age variables that Dr. Stiroh worries about. She also mentions the "negative coefficients on both the total number of new hires among the seven Defendants, the revenue per employee from the prior year, and the annual time trend." First and foremost, for the same reason that the coefficients on age are difficult to interpret, these coefficients are difficult to

^{53 &}quot;The counter-intuitive signs in Dr. Leamer's model are not limited to the variables related to age. The model also estimates negative coefficients on both the total number of new hires among the seven Defendants, the revenue per employee from the prior year, and the annual time trend. Taken at face value, Dr. Leamer's results imply that, all else equal, as the firms are doing more hiring, they pay their employees less. This runs contrary to basic economic principles and suggests that Dr. Leamer's model suffers from an endogeneity problem, in which case it is unreliable as an estimator of damages. The fact that the signs on the coefficients on revenue per employee and the time trend are also negative is counterintuitive and suggests an underlying problem with the model. As shown above, over the course of the Class period, the Defendants are expanding, revenue is growing, and total compensation per employee trends upward. The fact that Dr. Leamer's model suggests a negative relationship between these variables is unsupported by any economic theory that he has offered." Stiroh Report, par. 163.

- interpret because these variables compete with all the other variables in the equation to explain total compensation. For example, the time trend has to complete with other explanatory variables with a time trend, including the lagged total compensation variables.
- 73. Furthermore, the coefficients on both the time trend and the firm revenue variable have large standard errors, which mean that as far as these data are concerned these coefficients can be positive as well as negative. It isn't surprising that the time trend is not picking up the long-term upward trend in total real compensation because of the same collinearity problem there are other variables in the equation that capture that time effect.

6. When to Worry About Omitted Variables

74. For reasons that are explained in this section, (1) I have not been much concerned about the signs of the variables other than the CONDUCT variable (e.g. the age variable), (2) I have been concerned about the sign of the CONDUCT variable and its interactions with other variables since this is the basis for my damage estimate, (3) When the CONDUCT variable is interacted with another variable, I have been careful to include this interacting variable on its own, and (4) I have been very concerned about potential left-out variables that might be correlated with CONDUCT, which if omitted would be absorbed by the CONDUCT coefficient. These especially troubling left-out variables have approximately the same constant level during both the before and after periods and a different approximately constant level during the CONDUCT period.

D. Dr. Stiroh's Assessment of the Statistical Performance of My Damages Model is Inappropriate and Misleading

75. I have argued that corrections to the standard errors to adjust for clustering effects do not affect the estimated damages and thus do not really matter, since, a large standard error allows for the possibility that damages are either smaller or larger. Dr. Stiroh correctly points out that the adjusted standard errors leave the estimated conduct coefficient "statistically insignificant" at the conventional 5% level, but she inappropriately adopts the one-sided view that this proves

- there are no damages and not the other view that this proves the damages are really large.
- 76. Dr. Stiroh claims that the lack of statistical significance raises doubts regarding the reliability of these estimates and suggests that there may not be any damages at all.⁵⁴ She says that I am focusing on the wrong hypothetical when I dismiss the importance of the p-value associated with the conduct coefficient. She also argues that the majority of damages come from the two coefficients that aren't highly statistically significant, though this, as explained below, has no technically correct meaning.⁵⁵
- 77. It is perhaps worth pointing out that the statistical literature addresses two distinct problems: estimation and hypothesis testing. Entirely standard methods of presenting regression results, which I have adopted, address both the estimation problem and the hypothesis testing problem. The estimation problem is addressed by reporting regression coefficients and corresponding standard errors. The hypothesis testing problem is addressed by reporting t-values and p-values.
- 78. I have used the data to solve an estimation problem how to find the best estimate of damages. This has produced evidence, in the form of a regression result, that the damages are in fact most likely both positive and large. Dr. Stiroh only uses the data for one purported purpose, to test if there are damages at all. Given the abundance of evidence of the existence of agreements which had a sure byproduct of affecting levels of compensation, I do not think we have an hypothesis testing problem. But even if we do, Dr. Stiroh has not pursued the problem in a way that is appropriately sensitive to the issues in this case, something which I will explain in detail below.
- 79. Dr. Stiroh's limited approach is perfectly captured in the way she reports the regression results. She doesn't even report the standard errors. She reports only p-values. In her deposition, she reveals no knowledge of how to uncover the

⁵⁴ Stiroh Report, par. 167-172.

⁵⁵ Stiroh Report, par. 172.

standard errors from the p-values, and she allows some unstated book to do the testifying.⁵⁶ The real question is not what the formula is. The question is why she adopted such an unusual style of reporting. It must be that her expert opinions depend on p-values but not standard errors, since otherwise she is obligated to report them. I cannot recall ever seeing regressions reported with p-values and no standard errors. In other words she has tried to use the regression for one purpose only: to disprove impact, not to estimate it.

1. The Conduct Effects are Statistically Significant When the Context of this Case is Wisely Considered

- 80. Dr. Stiroh claims there is something wrong with my damage estimates when they are "statistically insignificant" or in her words statistically indistinguishable from zero at the conventional 5% level.⁵⁷ She puts forth this opinion even though her predecessor, Dr. Murphy, a far more experienced and accomplished economist, has already agreed this is wrong.⁵⁸ Dr. Stiroh admits she knows nothing about the origins of the 5% threshold. One of her own authorities, with whom I agree, explains, "there is no good reason why 5% should be preferred to some other percentage."⁵⁹
- 81. In this section, I explain why Dr. Stiroh's opinion is misguided, and Dr. Murphy's is correct in this one regard. The problem with Dr. Stiroh's opinion is that it depends on the choice of the level of statistical significance (e.g. 5%), but she has made no effort to connect her advice regarding the choice of significance level to the circumstances. She has "blindly followed" the conventional significance level, which is poorly suited to this case. The title of

⁵⁶ Stiroh Deposition, 245:14-25: "Q. How do you calculate P value from the standard errors? A. I don't remember the formula as I sit here. We can look it up in a book. Let's let the book testify as to what that formula is. I don't have it in my head. Q. Can you tell what the standard error is on a coefficient by looking at the P value? A. I don't remember if you can...[I] think you need another piece of information. But I just now, as I sit here, can't remember what the formulas are to go from one to the other."

⁵⁷ Stiroh Report, par. 167-170.

⁵⁸ Murphy Depo. at 366:14-17.

⁵⁹ Kennedy, Peter, A Guide to Econometrics (6th ed.), 60.

⁶⁰ Id.

Ziliak and McCloskey's book thus seems very pertinent: The Cult of Statistical Significance: How the Standard Error Costs Us Jobs, Justice, and Lives.⁶¹

- 82. In particular, Dr. Stiroh in choosing her significance level has ignored the abundance of documents that indicate the existence of these clandestine agreements and the role that the CEOs and the highest levels of management played in forming them. My conclusion from the documents and depositions is that these CEOs expected the agreements would help to keep employees from leaving, when the other way to keep them from leaving would have been to offer enough compensation that the employees wouldn't be interested in other jobs. In other words, I do not think the payroll data alone need to be used to prove that these agreements had an effect on compensation. The issue is how much. It might have been just a little, but zero is not a reasonable number given the documents that this case relies on. Nonetheless, I will discuss the testing of the hypothesis of no effect.
- 83. With that as the context we can turn to the choice of significance level. Putting aside the issue of legality of the agreements, there are two kinds of errors that might be committed when the final verdict is determined in this case. The first error would be to charge the defendants for damages when in fact there were no damages. The second error would be to fail to compensate the affected employees when in fact the agreements lowered their compensation. In statistical literature these are referred to as Type I and Type II errors. The two types of errors have an inverse relationship, i.e. the lower the Type I error is set, the higher is the probability of committing Type II error.⁶² The literature on

⁶¹ I venture the opinion that the profession has adopted the convention of testing at the significance level of 5% or 1% because that seems to allow conclusions to be free of the context. But the silliness of this enterprise led Stephen Ziliak and Dierdre McCloskey to write a book titled "The Cult of Statistical Significance." That book admirably lays out the history of the concept, which I will be happy to explain at trial. Nobel Laureate William Kruskal agrees that the 5% threshold is arbitrary and not always appropriate. Kruskal, Wm., "Significance, Tests of", INTERNATIONAL ENCYCLOPEDIA OF STATISTICS, v.ii (1978). In my own book, Specification Searches, I have a discussion of the choice of significance level that properly considers that probability of Type II error. Edward E. Leamer, "Specification Searches: Ad Hoc Inference with Nonexperimental Data", Wiley, i (1978)

⁶² Dr. Stiroh explained her awareness of this fact in the deposition. See Stiroh Deposition, 189:13-19: "...[T]here is an inverse relationship between the level of significance and -- which is the probability of making a type I error and the probability of making a type II error... If you are looking for significance at 1 percent,

- hypothesis testing treats the Type I error as more important either because there is substantial evidence beyond the data at hand that favor the hypothesis of no effect or because the costs associated with a Type I error are much greater than the costs associated with a Type II error.
- 84. Dr. Stiroh uses a significance level of 5%, which refers to the probability of the first error finding damages when the damages were zero. But what about the other error? When asked at the deposition what the relative costs of the two types of errors are, she only mentioned the cost of an error to the Defendants.⁶³ Unfortunately, the convention of setting the Type I error probability to 5% completely ignores the Type II error probability and completely neglects the legitimate interests of the employees in selecting the significance level.⁶⁴
- 85. Dr. Stiroh never mentions Type II error in her report, and expressed at deposition she had not calculated Type II error and didn't know how to.⁶⁵ However, it is not difficult to find the Type II error probabilities that correspond with Dr. Stiroh's advice of using 5% statistical significance level. Per my regression estimate in my Exhibit 3, the first-year impact of the agreements on wages of a 38 year old at a firm with a typical hiring rate is the coefficient on the CONDUCT variable, -0.0559. This implies that total compensation was reduced by 5.59%. The probability of the Type II error depends on the standard error of this CONDUCT coefficient which in my Exhibit 3 is 0.0447. I have used that information to form Figure 15 which

then there is a bigger chance of making a type II error."

⁶³ Stiroh Deposition, 192:8-193:5: "...Here, the cost that Dr. Leamer has alleged is about \$3 billion associated with him finding undercompensation, that certainly would be the cost to the defendant... of him being wrong... I don't know that there is something in a general sense that you evaluate the cost. It is in my view what is the cost of being wrong. And here it is measured, because it's a dollar value that is being attributed to the conduct at issue. And if, in fact, there is no impact, that dollar value is measured at \$3 billion."

⁶⁴ See Kruskal (1978), p. 952: "If significance tests are regarded as decision procedures, one criticism of them is based on the arbitrariness of level of significance and the lack of guidance in choosing that level."

⁶⁵ Dr. Stiroh expressed that she considered Type II error rate by choosing the conventional 5% level and by considering the specifications of the regression. This is circular and wrong. She did not understand the correct way to consider Type II error which is to consider the relative costs of the two kinds of errors. Stiroh Rough Dep. at pp. 189-195. ("Q. Is there a ...statistical procedure that one undertakes to measure the relative costs of type I and type II error? A. There may be...").

illustrates the Type II error probabilities as a function of the actual damage amount when the Type I error is set to 5%. Thus using Dr. Stiroh's advice, if the true undercompensation rate is 1%, the probability of wrongly saying there were no damages is almost 95%. Even if the first year effect were 10% the probability of finding in favor of the employees is still 40% compared with a Type I error that is only 5%. That in my opinion is seriously biased in favor of the Defendants.

- 86. Figure 16 illustrates the probability of a finding of no damage if the significance level is 50%. This has the appeal of putting the hypotheses of "no damages" and "small damages" on an equal footing both with a 50% probability of making an error. With this significance level there is a relatively small 6% chance of deciding in the favor the defense if actual damages were 10%. This seems to me to be the correct approach.
- 87. If the significance level is set at 50% to allow the probability of Type II error to take on reasonable values, the CONDUCT coefficient is statistically significant statistically different from zero.
- 88. Many analysts interpret p-values as a probability. There are two rather different schools of thought regarding inference from data the frequentist view and the Bayesian view and these have different ideas about how to interpret a p-value. From a frequentist standpoint, the p-value is the "just significance value." One is supposed to choose the significance level of an hypothesis test in advance and then either accept or reject the null hypothesis when the data arrive. If you chose .05, and rejected the null, you might be wondering what if you had chosen .01. If the p-value is .001, you would have rejected the null for any significance level above .001.
- 89. Bayesian statistics, on the other hand, has a mathematical philosophy of inference that allows the calculation of the probability that an effect is negative, while frequentists do not. Under certain circumstances, with a two-sided test like the ones implicitly used by Dr. Stiroh, when the estimate is negative, the probability that the coefficient is negative is 1- p/2 where p is the p-value. For the CONDUCT variable with a negative coefficient, the p value is 0.22, and the probability that the effect is negative (positive damages) is 1-(.22/2) = 0.89.

90. I strongly recommend the Bayesian approach, because it removes the statistician's arbitrary choice of significance level. Thus, regardless of where one sets the threshold for the p-value, the data simply tell us there is an 89% probability that the relationship we have hypothesized exists—in other words, far more likely than not. In the context of this data set, where we are attempting to estimate a complex relationship based on only approximately 60 effective data observations, this result is highly *economically* significant given the magnitude of the estimated harm to the employees and the facts and economic theory that tell us such harm would have occurred, and that a null hypothesis of zero impact is *a priori* probably wrong. That is why I have never depended on p values or "statistical significance" to support my conclusions in this case.

Probability of Wrongly Finding NO Damages
When The Probability of Wrongly Finding Damages is 5%

Alligned A.

Alligned A.

Damages as Percent of Total Compensation

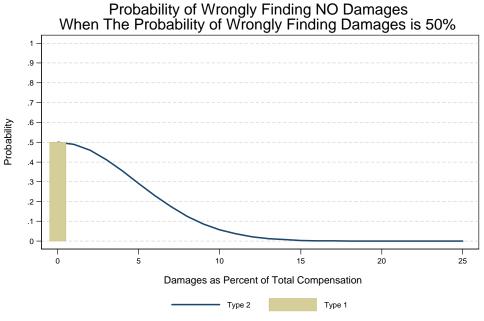
Type 2

Type 1

Figure 15: Dr. Stiroh's Error Probability

Note: Based on -0.0559 Estimate and 0.0447 Robust St. Error of the Conduct coefficient Source: Learner Merits Report, Exhibit 3

Figure 16 A Better Curve of Type II Error Probabilities



Note: Based on -0.0559 Estimate and 0.0447 Robust St. Error of the Conduct coefficient Source: Leamer Merits Report, Exhibit 3

E. Dr. Stiroh's Claims about Omitted Variables are Strictly Hypothetical and Ignore My Efforts to Include All Relevant Variables

"Numerous events occurred in the Class period that affected compensation at the Defendants' firms, independent of any alleged "conduct" but are unaccounted for in Dr. Leamer's model. For example, the model does not account for the impact of the 2008-2009 recession during the alleged Class period. It does not allow for variation in how each of the Defendants responded to the recession when setting compensation. It cannot identify employees who continued to receive pay increases based on cold-calls or raises due to pressure from non-Defendant rival employers. And, it conflates the impact, if any, of the challenged agreements with the impact of concurrent agreements with similar terms that are not at issue in this case. The inability of Dr. Leamer's model to disentangle the impact of the alleged conduct at issue from the effect of independent events on compensation makes his damage model unreliable and entirely incapable of measuring the effect of the alleged conduct at issue." 66

1. My Model Controls for Individual, Market and Firm-Specific Factors Effecting Compensation

- 91. Dr. Stiroh is incorrect in saying that my model omits unspecified market variables and does not control for the effect of the 2008-2009 recession. Firm revenue, firm hiring, and San Jose Information sector hiring are all highly pertinent market and firm-specific recession-sensitive variables. The variable against which Dr. Stiroh mounts her most tenacious attack, the number of new hires, is picking up a post-recession effect on the Defendant firms. In an alternative models which I presented as Exhibit 4 to my Leamer Damages Report,⁶⁷ I added stock prices and firm profit which are also this category of variable. All of these variables are candidates for macro-economic controls. If Dr. Stiroh wanted to be constructive she would name the variables and show how the variable mattered. Otherwise her comment is merely hypothetical.
- 92. I present a sensitivity test for my model here in answer to Dr. Stiroh's criticism that the recession has not been accounted for. Dr. Murphy recommended the use of a market-wide stock index to measure general economic and financial performance in the economy.⁶⁸ Exhibit 4 is a version of my model with the inclusion of the change in the annual average S&P 500 Index as a macroeconomic control variable (not the end of year value proposed by Dr. Murphy). My damages estimates are not substantially affected by this inclusion.
- 93. In light of the various macro-economic variables already included in my model and this sensitivity test, there does not appear to be any reason to suspect that the model does not adequately control for recessions.

⁶⁶ Stiroh Report, par. 7.i.

⁶⁷ I present this model again below.

⁶⁸ Murphy Report, par. 138.

2. Dr. Stiroh Proposes So Many New Variables that the Data are Overwhelmed and Her Estimates are Statistically Unreliable

- 94. Dr. Stiroh criticizes my model for not incorporating fixed effects for titles and also an indicator variable for promotions (title changes). Fixed effects and promotions are unnecessary and inappropriate in this model. The title structures are used by each of these defendants for hierarchical control of compensation in each firm but whatever effect these structures have on compensation it is completely embodied in the compensation history of individual employees which is why I have chosen to study individual data. I fail to see how it is material if an individual was always in the same title, or moved between titles. Compensation increases can come either within or between titles. What matters is the compensation path.
- 95. My model has lagged dependent variables. Lagged dependent variables play a role similar to individual fixed effects which would more than compensate the lack of title fixed effects. In the common impact analysis I presented in my original report, the goal was to explain cross-sectional variation in compensation and title fixed effects were appropriate there. In the damages model, where the dynamics are critical, they do not have a place.
- 96. Moreover, Dr. Stiroh did not even attempt to investigate the type of deficiency she is suggesting. I investigated two different ways of trying to capture promotions and title changes in my model and both leave my conclusions unaffected. The first attempt I made along these lines was in response to Dr. Stiroh's criticism that my model does not attribute compensation changes associated with title changes to the change in the title. Hence, I ran a variation of my model including a control variable for years in which the employee experiences a title change from the previous year. This assumes that promotions were not affected by the Non-Compete Agreements. This model is presented in Exhibit 6 and again the resulting damages estimate are barely different than the original.
- 97. My second test for sensitivity to promotions was with respect to the model with one lag of compensation presented in Table 6. I computed a version of that model dropping the years in which employees experience a title change. This

leaves damages effectively unchanged from the total computed under that model as well. Both these variations suggest that title changes are not likely to be a critical factor to account for in the damages model.

F. Dr. Stiroh's Decomposition of Damages into Three Parts is Completely Inappropriate

- 98. The decomposition of damages into three parts reported in Exhibit V.12 is meaningless and the fact that Dr. Stiroh puts this forward raises a very large red flag about her competence. The reason it is meaningless is because this part of my damage model has a separate CONDUCT variable and also the CONDUCT variable interacted with other variables. These interactive models do not allow meaningful linear decompositions such as the one offered by Dr. Stiroh. The problem is that mathematically identical interactive models yield different decompositions.
- 99. To make this clear, suppose we began with the model

Total Comp_i =
$$\alpha + \beta \times CONDUCT_i + \lambda \times CONDUCT_i \times AGE_i$$

where × means "times", the subscript *i* indexes employees, CONDUCT is a binary variable indicating the presence of the noncompete agreements and α , β and λ are coefficients to be estimated from the data. The total damages per this equation during the period in which the CONDUCT variable is equal to one, is $n \times (\beta + \lambda \times \text{Average Age})$, where n is the number of affected employees. This seems to support the decomposition: $n \times \beta$ from the first variable and $n \times \lambda$ × Average Age from the second variable

100. But β in this model is the impact of the agreements when the second term drops out, that is to say when AGE is zero. Since there are no babies in this data set, I chose instead to measure the age around the average age equal to 38, thus replacing AGE in the equation with AGE* = AGE-38. The allows us to interpret the CONDUCT coefficient as the impact on a 38 year old. We can find the same equation with the new variable AGE* by replacing AGE with AGE*+38:

Total Comp $i = \alpha + \beta \times CONDUCT i + \lambda \times CONDUCT i \times (AGE*I + 38)$

= Total Comp i =
$$\alpha$$
 + (β +38 λ)×CONDUCT i + λ ×CONDUCT i ×AGE* I

- 101. In this form, the decomposition suggests a first effect equal to $n \times (\beta + 38 \lambda)$ and a second effect equal to $n \times \lambda \times Average Age^*$, where Average A* is the average departure from 38 years.
- 102. Thus although these two models are mathematically identical, they have different coefficients on the CONDUCT variable, different measures of statistical significance on that coefficient, and different decompositions. It doesn't make any sense to do this.

VI. Dr. Stiroh's Study of the Sensitivity of Damages to Choice of Model is seriously flawed and mostly irrelevant

"The model is not robust to changes in specification and as a result 'damages' are greatly diminished or eliminated entirely when minor changes are made to the specification. Adjusting the model to correct certain flaws in the model result in no Class-wide impact from these agreements." ⁶⁹

"Reasonable alterations to Dr. Leamer's model substantially change the estimated damages figure and cast serious doubt on the model's ability to properly assign damages. Adjusting Dr. Leamer's model to use nominal figures, as employers did not have perfect information about the future inflation prior to setting compensation, substantially reduces what he believes to be damages caused by the alleged conduct. Similarly, adjusting to allow for varying impact of conduct by firm, as compensation practices differ at each firm, substantially reduces or eliminates the alleged damages. And, adjusting Dr. Leamer's model to isolate the impact of hiring at firms with a DNCC agreement from the

⁶⁹ Stiroh Report, par. 7.f.

impact of hiring at firms without a DNCC agreement, substantially reduces or eliminates the purported damages."⁷⁰

A. A Sensitivity Analysis to Explore Model Ambiguity Error Needs to be Conducted Wisely.

103. An unobtainable ideal with non-experimental data is an estimate that has a very small standard error and that does not depend much on details of the model. In a previous section I have provided my opinion regarding the sampling error that applies to the damage estimate. Here I will comment on the model ambiguity concerns which can be unearthed by changes in the model, in other words a sensitivity analysis.

1. Perturbations of the Model Must Make Economic Sense

- 104. A sensitivity analysis can be conducted either by shrinking or by expanding the model. Shrinkage of a model by exclusion of variables needs to be explored only when there is substantial doubt about the inclusion of an effect, and only if whatever doubt might have existed is not relieved by a high enough t-value on the doubtful coefficient. In other words, if the data strongly say the variable belongs, the analyst needs to accept it. For that reason, except in rare instances the exclusion of a variable whose estimated coefficient has a small standard error should be avoided, even if the coefficient has the "wrong" sign. It should already be clear from the discussion of Dr. Stiroh's mistakes about the sign of the age variable that an analyst needs to have a high level of humility when it comes to wrong signs since knowledge of signs is severely limited in multivariate regressions. Furthermore, the proper treatment of a genuinely wrong sign that is statistically significant is not to constrain the offending coefficient to zero (e.g. dropping the variable) but to find the additional variable that is causing this wrong sign.
- 105. A sensitivity analysis can also be conducted by expanding the model by including additional variables. This has to be done with a large dose of wisdom.

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⁷⁰ Stiroh Report, par. 7.g.

Additional variables should be explored but only ones that genuinely belong in the model. There are literally thousands of macroeconomic variables and different lag structures and different functional forms, and it is a virtual certainty that there are many variables out there that will destroy a regression result. If one variable by itself doesn't do the job, try ten and if ten don't do the job, try one hundred. That's not progress. That's just a fishing expedition.

VII. Dr. Stiroh's Sensitivity Analysis is Misleading.

A. Dr. Stiroh's First Alternative, a "Stepwise" Regression Model, is Inappropriate

- 106. Dr. Stiroh has found her first alternative model reported in Exhibit V.14 by omitting the CONDUCT related variables that are statistically insignificant at traditional significance levels, and thus retaining only the age related CONDUCT effects. This method is what is known as "stepwise" regression which is rarely used by econometricians because it has great power to mislead. Dr. Stiroh's own preferred textbook on econometrics makes the same point.⁷¹
- 107. The use of stepwise regression by Dr. Stiroh is a great example of the trouble it can create, because the age related variables that are retained in the equation have been designed by me to take on the value of zero when age is 38, which allows the coefficient on the CONDUCT variable to measure the impact on a 38 year old. But when the CONDUCT variable is dropped as Dr. Stiroh has done, it creates a model that *by assumption* imposes zero damages for 38 year olds. I am sure Dr. Stiroh didn't realize what she has done here, but her use of stepwise regression to make a point casts doubt on her ability to serve as a fair and unbiased and qualified expert, or at least one of those qualities.

⁷¹ Kennedy, Peter, A Guide to Econometrics (6th ed.), 49. ("A variant of OLS called *stepwise regression* is to be avoided. ... We don't rely on stepwise regression or any other automated statistical pattern recognition to pull understanding from our data sets because there is currently no way of providing the critical contextual inputs into these algorithms and because an understanding of the context is absolutely critical to making sense of our noisy non-experimental data.") (emphasis in original).

B. Dr. Stiroh's Second Alternative, a Nominal Compensation Regression Model is Inappropriate

- 108. Real compensation adjusts for inflation effects by dividing the value of compensation by a measure of the price level, the CPI in my model. Dr. Stiroh's second model reported in Exhibit VI.1 replaces my real compensation with the unadjusted nominal figures. She justifies this because "employers did not have perfect information about the future inflation prior to setting compensation."
- 109. Actually there is nothing "future" in my model which divides annual compensation figures with the annual average of monthly CPI levels, matching numerator and denominator year by year. It is possible that Dr. Stiroh wants this matching to be done month by month or day by day, though this is not what she has written.
- 110. Even if her words were valid, the complete absence of any CPI variables in Dr. Stiroh's equation reported in Exhibit VI.1 is a huge mistake. Competitive models of the labor market set wages equal to the value of the marginal product. Equivalently real wages are equal to the marginal product. The labor market is thus assumed to determine real wages, not nominal wages. It takes a macro economic model with money to determine the levels of wages and levels of prices separately. Thus Dr. Stiroh's equation is a huge departure from mainstream economics thinking because by completely excluding any price levels in her equation she is assuming the labor market determines nominal wages, not real wages.

C. Dr. Stiroh's Third Alternative Model Inappropriately Changes the Start year of the Intel Agreements

- 111. As described above, this proposed change to the start date of the Intel agreements is unsupported by the evidence. It is alleged and clear from the documents that Intel was a participant in the agreements prior to 2006. As such this is not a valid sensitivity check.
- 112. In a before-and-after model, changing the date of the conspiracy would be expected to have substantial changes in the measured effect of the conduct. It's not just that a portion of Intel's employment is being removed from the class,

but that some suppressed compensation is then being treated as "normal", making other suppressed compensation appear more appropriate. Unsupported changes to the Agreement dates should not be made for sensitivity analysis or the convenience of exposition.

D. Dr. Stiroh's Fourth Alternative Model Overwhelms the Data by Disaggregating Across Defendants

113. Dr. Stiroh disaggregates the effect of the Non-Compete Agreements by interacting the conduct variable with firm indicator variables. As I wrote in an earlier report in response to Dr. Murphy's disaggregation:

In my model I allow some amount of variability in the CONDUCT effect across Defendants depending on their rates of hiring. In my model, I have allowed for the lagged dependent variables to vary by Defendant because it became apparent that the time series patterns were different, especially for the Google data. If I were going to disaggregate one more effect it would be revenue, based on the idea that these seven firms might have had different approaches to sharing their revenue gains with their employees. In other words, disaggregation requires better judgment than just throwing an excessive set of additional variables into the model, as Dr. Murphy has done.⁷²

114. Perhaps the best way to make the point is to think of the data as a resource that needs to be devoted to answering a set of questions. The data are capable of answering a few questions, but if you ask too many questions the limited evidence is spread too thin, and will push back by giving you wild estimates with large standard errors. The data are capable of answering the question: "What is the general impact of these agreements?" but the data falter when asked the question "What is the impact on each Defendant workforce of these agreements?" Dr. Stiroh has asked that question but she has silenced the alarm

⁷² Leamer Cert Reply Report, par. 102.

that data would have rung out by not reporting and not looking at standard errors. If she had, she might have sought some middle ground between these two extremes, allowing some freedom but not complete freedom for the defendant effects to vary, which has been my approach.

E. Dr. Stiroh's Next Four Models Inappropriately Attack the Most Significant Variable: New Hires

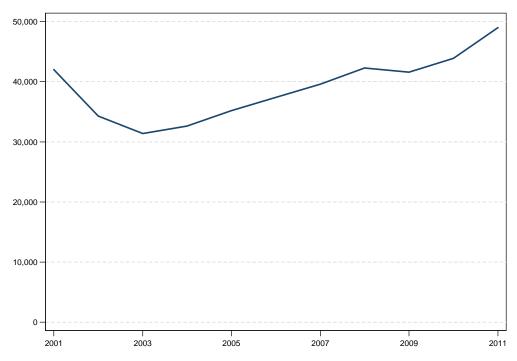
- 115. In 1975 I published an article⁷³ in which I demonstrated that when a variable with a certain t-value is omitted from a regression equation, the signs of the coefficients in the new equation will be same as before for any variable with a larger absolute t-value. To put this another way if you want to wreak havoc on the coefficients, omit the variable with the largest absolute t-value. Here it is the log of total number of new hires that has the largest absolute t-value other than the persistence effects captured by the lagged total compensation variables. Dr. Stiroh focuses her attention on this variable, estimating eight different regressions removing this variable and replacing it each time with one of three different sets of variables.
- 116. The premise of her attack is that this variable has what she considers to be the "wrong" sign. I consider this highly inappropriate and quite presumptuous since it presumes knowledge of the sign of this effect that exceeds the knowledge embedded in the data, which is substantial, yet I do not think that Dr. Stiroh actually has this knowledge, just as she clearly doesn't have the knowledge of the sign of the age variable.
- 117. In other words, if she doesn't like the sign of this coefficient, then she needs to find another variable that makes the sign "correct" itself. She can't just throw away the most statistically significant variable and wreak havoc on all the other coefficients.
- 118. I have enough experience with empirical work to know that the upward sloping age-earnings profile, which is surely in the data, is also surely embodied in any

⁷³ Edward Leamer, "A Result on the Sign of Restricted Least Squares Estimates," Journal of Econometrics, 3 (1975), 387-390.

regression estimated with these data. Thus I knew the age variables had the "right" sign even though they appeared "wrong." The statistically significant coefficient on the number of new hires concerned me too, since like Dr. Stiroh I thought the sign seemed to be "wrong." But I couldn't identify what might be the left out variable that would be powerful enough (a larger t-value) to correct this very entrenched "problem." The data insisted and I relented by rethinking the sign on this variable which now seems quite "right" not wrong.

119. In fact there is a quite plausible explanation for the behavior of the data. The normal aftermath of a recession has a period of elevated hiring rates when workers laid off in the recession are recalled to their previous jobs or similar jobs. Only later, when the hiring has been enough to drive down the unemployment does the labor market tighten enough to put upward pressure on wages. Figure 17 and Figure 18, below, support the post-recession interpretation of the negative coefficient on new hires. Employment in the information sector didn't recover to its 2001 level after the tech bust until 2008. The hiring in 2004 and some of the hiring in 2005 was likely recalls of previous tech workers. The spike up in the defendant's new hire variable in 2005 and again in 2010 and maybe 2011 probably coincided with a period during which workers who previously lost jobs were finding them again. Thus the variable is (surprisingly) identifying periods of weak labor markets not strong ones.

Figure 17: San Jose Information Sector Employment



Source: St. Louis Federal Reserve

Figure 18: Defendant Hiring vs. Change in San Jose Information Sector Employment

Source: Defendant Employee Data and St. Louis Federal Reserve

120. The second explanation relates to the negotiating position during times of hiring. High levels of hiring may leave the impression that replacements are easy to find, and tend to hold down wages of incumbents.. The message of this discussion of both the age coefficients and the new hire coefficients is one word: humility. Especially when the variable in question has the highest t-value.

1. Dr. Stiroh's Preferred Model Inappropriately Drops the New Hires Variable and Inserts a Doubtful Median Wage Variable

121. Dr. Stiroh criticizes my use of total new hires by Defendants as a measure of Defendants' demand for employees. The variable, as shown above captures important features of the competitive circumstances facing the Defendants-including the uptick in their demand that occurred in 2005. In place of this variable Dr. Stiroh uses median wages in the tech sector. She described the purpose of this variable to capture "upward pressure on wages due to the

market."⁷⁴ Dr. Stiroh admitted at deposition that she has made a fundamental error by believing that the total new hires variable controls for effects of the industry on compensation when in fact it only contains data from the Defendants, and is identified in my prior work as an "employer effect" variable. The variable she adds is a true "industry effect" variable and not a proper substitute. I have already controlled for industry effects using the San Jose MSA employment figure, with which Dr. Stiroh apparently has no quarrel.

- 122. Dr. Stiroh's median wage data come from the Current Population Survey (CPS), which is a monthly survey of households. This worries me for several reasons.
- 123. Firstly, for estimating median earnings for specific categories of employment, sample size concerns with the CPS are elevated. I wonder how many observations are in the categories that Dr. Stiroh uses: "Computer and Peripheral Equipment Manufacturing" and "Computer Systems Design and Related Services." I also wonder if these categories have much to do with the Defendant technical class workers. These make no clear reference to software engineers. I know that when I worked for IBM there was a distinct separation between system design and software coding.
- 124. Secondly, the accuracy of the reported earnings is questionable. When the Census approaches a household they have one respondent who reports income and employment for each members of the household. The income response is entirely from memory. The income question in the CPS is:⁷⁵

Which category represents (your/name of reference person/the total combined income) (total combined income during the past 12 months?/ of all members of your FAMILY during the past 12 months?/ of all members of (name of reference person) 's FAMILY during the past 12 months?)

This includes money from jobs, net income from

This includes money from jobs, net income from

⁷⁵ Basic CPS Questionaire, Labor Force Items, http://www.census.gov/cps/files/questionnaire/Labor%20Force.pdf

⁷⁴ Stiroh Report, fn.282 and 283.

business, farm or rent, pensions, dividends, interest, social security payments and any other money income received (. / by members of (your/ name of reference person) FAMILY who are 15 years of age or older.)

1 Less than \$5,000

2 5,000 to 7,499

3 7,500 to 9,999

[and so on.]

- 125. Thirdly, Dr. Stiroh's data spans an industry classification which includes companies and jobs that are too broad for the class definition. Specifically, Dr. Stiroh's analysis relies on median wages in "Computer and Peripheral Equipment Manufacturing" and "Computer Systems Design and Related Services." The above industries correspond to Census industry codes 3360 and 7380 which map to NAICS codes 3341 and 5415.
- 126. The use of median broad industry data for occupational wage analysis is problematic because 1) the industry classifications selected by Dr. Stiroh are too broad and include companies in industries that are unrelated to the class⁷⁸ and 2) the industry classification issues only one NAICS code per company, which

⁷⁶ Dr. Stiroh uses median 2001 – 2011 wage of the combined industries comprising "Computer and Peripheral Equipment Manufacturing" and "Computer Systems Design and Related Services," Stiroh report, Exhibit VI.10.

⁷⁷ In the 2002 CPS survey, the following industries were mapped to Computer and Peripheral Equipment Manufacturing (3360): 321-Office and accounting machines (1987 SIC Code equivalent 3578-3579), 322 - Computers and related equipment (1987 SIC Code equivalent 3571-3577). The following industry was mapped to Computer Systems Design and Related Services (7380): 732 - Computer and data processing services (1987 SIC Code equivalent 737). Industry codes 3360 and 7380 were used in the 2007 Census Industrial Classification, which is based on the 2007 North American Industry Classification System (NAICS). Thus, Census codes 3360 and 7380 correspond to NAICS 3341 and 5415, see Occupational and industry classification systems in CPS data at http://www.bls.gov/cps/cpsoccind.htm and 2007 Census Industrial Classification-2007 NAICS crosswalk at http://www.bls.gov/cps/cenind.pdf.

⁷⁸ The sub-industries contained within NAICS 3341 and 5415 are listed below. Just based on the industry descriptions it appears that the industries selected by Dr. Stiroh are too broad and capture many more occupations besides software developers. 3341 - Computer and Peripheral Equipment Manufacturing (equivalent to 2007 Census 3360): 33411 - Computer and Peripheral Equipment Manufacturing, 334111 - Electronic Computer Manufacturing, 334112 Computer Storage Device Manufacturing, 334113 - Computer Terminal Manufacturing, 334119 - Other Computer Peripheral Equipment Manufacturing. 5415 - Computer Systems Design and Related Services (equivalent to 2007 Census 7380): 54151 - Computer Systems Design and Related Services, 541511 - Custom Computer Programming Services, 541512 - Computer Systems Design Services, 541513 - Computer Facilities Management Services, 541519 - Other Computer Related Services. http://www.census.gov/eos/www/naics/index.html.

suggests that median industry wage data likely contain compensation for employees holding positions that are not relevant to the class. Under the NAICS industry classification system each company is assigned one industry code based on its primary activity, and the compensation of all employees is classified under the same code regardless of their occupation.⁷⁹ On the other hand, in the Standard Occupational Classification (SOC) survey, which I use in my analysis, average or median compensation data are reported based on Standard Occupation Code (SOC), regardless of the company's primary activity.⁸⁰

- 127. In summary, I am extremely doubtful about the usefulness of this median wage variable, and it surely isn't a substitute for the number of new hires which Dr. Stiroh inappropriately omits when she adds this median wage variable. This median wage variable competes with the other industry effect in my model: employment in the information sector. Also this market salary variable does not measure well the circumstances faced by these top firms. The new hires variable was statistically important and did capture that effect. Consequently a more appropriate sensitivity is to keep the total new hires variable and add an appropriate form of a variable to capture "upward pressure on wages due to the market."
- 128. If Dr. Stiroh thinks we need an additional industry variable, which we do not, such data is available in the form of a BLS occupation wage series. The

⁷⁹ According to a Census FAQ page about NAICS, "the U.S. Census Bureau assigns and maintains only one NAICS code for each establishment based on its primary activity (generally the activity that generates the most revenue for the establishment." Also, NAICS doesn't track occupations, "the NAICS system is used to classify establishments according to their primary industrial activity. It is not a system for classifying occupations." See http://www.census.gov/eos/www/naics/faqs/faqs.html#q16 and http://www.census.gov/eos/www/naics/faqs/faqs.html#q19.

^{80 &}quot;Because the Census occupational and industry classifications are adaptations of the SOC and NAICS, occupational and industry statistics from the CPS are not strictly comparable with statistics from other sources that use the SOC and NAICS directly." See http://www.bls.gov/cps/cpsoccind.htm. In the Standard Occupational Classification (SOC) system "[a]ll workers are classified into one of 840 detailed occupations according to their occupational definition. To facilitate classification, detailed occupations are combined to form 461 broad occupations, 97 minor groups, and 23 major groups. Detailed occupations in the SOC with similar job duties, and in some cases skills, education, and/or training, are grouped together." See http://www.bls.gov/soc/.

Occupational Employment Statistics (OES) is a biannual survey of establishments with a large sample size and it does not include supplemental compensation.⁸¹ I selected four occupation categories from this data and compiles a software wage series.⁸²

129. I find that adding the more appropriate market compensation variable (salaries of software occupations) to the model while retaining the total new hires variable does not undermine my damages estimates. This tells me that no evidence exists to use Dr. Stiroh's variable in place of the San Jose MSA unemployment variable I have already chosen.

Figure 19: Dr. Stiroh's Median Wage is Not a Substitute for Defendant Hiring

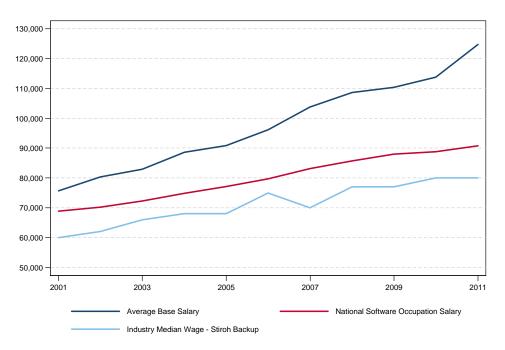


Source: Defendant Employee Data, Stiroh Backup

⁸¹ http://www.bls.gov/oes/oes ques.htm

⁸² The four categories are: Computer and Information Research Scientists; Computer Programmers; Software Developers, Applications; Software Developers, Systems Software

Figure 20: Dr. Stiroh's Median Wage Does Not Track Defendant Compensation Closely



Source: Defendant Employee Data, Stiroh Backup, BLS

Table 8: Damage Sensitivities Estimates

Model	Conduct- Age Interaction	Conduct- Age Sq Interaction	Conduct- Hiring Interaction	Conduct	Total Class Damages (\$ Billion)
1. Leamer Model	1.174	-0.159	-0.017	-0.056	3.050
2. Model with One Lag	1.223	-0.164	-0.047	-0.087	3.800
3. Model with Change in S&P 500 Indicator	1.174	-0.159	-0.017	-0.057	3.105
4. Model with Market Salary for Software Occupations	1.163	-0.157	-0.017	-0.076	4.237
5. Model with Control for Title Change	1.179	-0.159	-0.017	-0.058	3.172
6. Model with One Lag & No Change in Title	0.653	-0.087	-0.042	-0.085	3.784
7. Bilateral Conduct Variable	2.060	-0.284	-0.039	-0.136	2.872
8. Dr. Stiroh's Split Hiring model with Total New Hires	1.146	-0.155	-0.011	-0.046	2.683
9. Dr. Stiroh's Split Hiring (scaled) model with Total	1.184	-0.160	-0.018	-0.057	3.115
New Hires					
10. Model with Separate Conduct Effect for California	1.172	-0.158	-0.016	-0.054	3.052
11. Intel Hardware Sensitivity	1.221	-0.164	0.018	-0.053	4.167
12. Model with Stock Prices and Lagged Profits ¹	0.985	-0.134	-0.057	-0.115	4.811

Note: 1 Excludes Pixar and Lucasfilm

Source: Defendants' employee compensation data; Damages Regression Results

Table 9 Dr. Stiroh's Regression Results

	Conduct-	Conduct-	Conduct-		
	Age	Age Sq	Hiring		Total Class
Model	Interaction	Interaction	Interaction	Conduct	Damages
					(\$ Billion)
1. Compensation Regression	1.177	-0.159	-0.017	-0.056	3.064
2. Only Statistically Significant Conduct Variables					0.414
3. Only Age-Conduct Interaction	2.532	-0.344			0.910
4. Using Nominal Figures	1.203	-0.162	-0.018	-0.034	1.761
5. Assuming Intel's conduct began in 2006	1.284	-0.174	-0.010	-0.033	1.778
6. Disaggregating Conduct by Defendant ¹					1.169
7. Splitting Total New Hires Variable	0.847	-0.116	0.013	0.533	0.543
8. Replacing Total New Hires with Median Wage	1.062	-0.143	-0.014	0.048	-3.003
9. Splitting Total New Hires Variable into Shares	0.938	-0.128	-0.036	0.044	-0.875
10. Splitting Total New Hires Variable into Shares	1.103	-0.151	0.026	0.004	-1.328
Assuming Intel's Conduct Began in 2006					
11. Conduct Interaction with Annual Indicators ¹	1.215	-0.164	-0.017		1.630

Note: ¹ Disaggregated Coefficients not presented Source: Stiroh Report

2. Stiroh's Modifications of the "Total Number of New Hires" Variable Are Disguised Ways of Omitting this variable

- 130. While Dr. Stiroh claims that she makes only "minor" modifications to the original regression, her modifications in Exhibits VI.7, VI.11, and VI.14 (VI.14 also modifies the Intel Conduct to start in 2006 which is addressed elsewhere) are actually rather substantial. Dr. Stiroh removes one of the original variables and includes 3 different variables, one of which is interacted with the conduct, thus materially changing the way the conduct effect is computed. Dr. Stiroh does two versions, one with the number of new hires and the other new hires as a share of current year employees. Dr. Stiroh makes the following modifications to the regression model.
 - i. Remove Log(Total Number of New Hires) variable
 - ii. Include "Log(Total Number of New Hires of DNCC firm)" variable. This variable is computed as number of hires of the firm(s) with which a particular defendant had agreements. For example, for ADOBE it is computed as the total number of hires by APPLE in each year.

- iii. Include "Log(Total Number of New Hires of Non-DNCC firms)" variable. This variable is computed as number of hires of the firm(s) with which a particular defendant had no agreements. For example, for ADOBE it is computed as the total number of hires by all non-APPLE defendants.
- iv. Include "Conduct * Log(Total Number of New Hires of DNCC firm)" variable. 83
- 131. The "Total Number of New Hires" variable was included in the original model as a macro-factor to control for the overall demand for labor by all defendants. In addition, the model included a different variable of hiring by each firm. Dr. Stiroh's broken-down hiring variables only partially capture the overall demand and add nothing to the model. If one wanted to really make a "minor" modification of the analysis to check the effect of Dr. Stiroh's variables, those variables would simply be added to the original regression. Below is the result of this regression. This model shows that Dr. Stiroh's added variables are statistically insignificant while the "Total Number of New Hires" remains statistically significant.

⁸³ Stiroh Report, par. 182-191; Exhibit VI.1, VI.11, and VI. 14.

Table 10: Dr. Stiroh's Hiring Split variable Regression with Total New Hires II

Observation: Employee ID record in December of each year Dependant Variable: Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1459 ***	0.4352	2.6333
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1551 ***	0.0572	-2.7113
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0107	0.0371	-0.2883
4. Conduct	-0.0458	0.0463	-0.9887
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6628 ***	0.0602	11.0092
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7297 ***	0.0576	12.6789
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4341 ***	0.0734	5.9129
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6790 ***	0.0337	20.1229
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6484 ***	0.0518	12.5269
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9546 ***	0.0942	10.1300
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6716 ***	0.1490	4.5077
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3108 ***	0.0451	6.8859
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2444 ***	0.0404	6.0533
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3662 ***	0.0486	7.5392
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2870 ***	0.0295	9.7445
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3075 ***	0.0463	6.6470
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0140	0.0988	0.1413
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0934	0.1186	0.7875
19. Log(Age) (Years)	-0.6481 ***	0.1954	-3.3171
20. Log(Age)^2	0.0781 ***	0.0250	3.1285
21. Log(Company Tenure) (Months)	0.0111	0.0437	0.2531
22. Log(Company Tenure)^2	-0.0005	0.0045	-0.1052
23. Male	0.0054 **	0.0025	2.2089
24. DLog(Information Sector Employment in San-Jose)	1.8765 ***	0.5379	3.4884
25. Log(Total Number of Transfers Among Defendants)	0.1049 ***	0.0372	2.8191
26. Year (trend)	-0.0025	0.0084	-0.2976
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0090	0.0424	0.2128
28. Log(Total Number of DNCC New Hires)	-0.0167	0.0410	-0.4059
29. Log(Total Number of non-DNCC New Hires)	-0.0359	0.0653	-0.5491
30. Log(Total Number of New Hires)	-0.2784 ***	0.0831	-3.3508
31. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0775	0.0870	-0.8903
32. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1567 *	0.0917	1.7090
33. APPLE	0.1073	0.2726	0.3937
34. GOOGLE	1.3015 ***	0.5205	2.5002
35. INTEL	0.0299	0.2936	0.1017
36. INTUIT	0.0935	0.2216	0.4219
37. LUCASFILM	0.0601	0.3051	0.1970
38. PIXAR	1.3475 ***	0.3885	3.4686
39. Location (State) Indicators	YES	0.3003	5.4000
40. Constant	YES		
R-Square	0.868		
N-5quare Observations	277,082		
Obstivations	277,002		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Table 11: Dr. Stiroh's Hiring Split variable Regression with Total New Hires

Observation: Employee ID record in December of each year Dependant Variable: Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1841 ***	0.4489	2.6378
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1598 ***	0.0590	-2.7073
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0177	0.0365	-0.4851
4. Conduct	-0.0573	0.0460	-1.2454
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6789 ***	0.0552	12.2912
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7293 ***	0.0578	12.6203
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4339 ***	0.0741	5.8526
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6824 ***	0.0336	20.2875
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6521 ***	0.0507	12.8708
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9200 ***	0.0840	10.9487
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6747 ***	0.1471	4.5849
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2947 ***	0.0444	6.6435
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2460 ***	0.0404	6.0956
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3684 ***	0.0504	7.3154
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2835 ***	0.0288	9.8417
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3050 ***	0.0457	6.6779
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0595	0.0875	0.6794
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0944	0.1165	0.8098
19. Log(Age) (Years)	-0.6590 ***	0.1992	-3.3088
20. Log(Age)^2	0.0793 ***	0.0254	3.1208
21. Log(Company Tenure) (Months)	0.0218	0.0447	0.4892
22. Log(Company Tenure)^2	-0.0017	0.0046	-0.3588
23. Male	0.0058 **	0.0026	2.2539
24. DLog(Information Sector Employment in San-Jose)	1.8764 ***	0.5445	3.4464
25. Log(Total Number of Transfers Among Defendants)	0.1005 ***	0.0374	2.6900
26. Year (trend)	-0.0044	0.0086	-0.5035
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0268	0.0360	0.7455
28. Log(Total Number of DNCC New Hires/Number of Employees)	0.0088	0.0407	0.2169
29. Log(Total Number of non-DNCC New Hires/Number of Employees)	0.0003	0.0440	0.0068
30. Log(Total Number of New Hires)	-0.3412 ***	0.0719	-4.7432
31. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0374	0.0825	-0.4530
32. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1297	0.0863	1.5017
33. APPLE	0.0711	0.2767	0.2569
34. GOOGLE	1.3059 ***	0.5152	2.5345
35. INTEL	0.0814	0.3008	0.2706
36. INTUIT	0.0872	0.2209	0.3947
37. LUCASFILM	-0.0137	0.3227	-0.0423
38. PIXAR	1.3225 ***	0.3934	3.3618
39. Location (State) Indicators	YES	0.0201	3,5010
40. Constant	YES		
R-Square	0.868		
Observations	277,082		
Observations	211,002		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

As I described above, if one were to accept the view of the Non-Compete Agreements as a collection of bilateral agreements, an imperfect--but implementable--alternative would be to assume that the effect of the Agreements is proportional to the mobility foreclosed. The sensitivity of the regression to this issue can be tested using the number of employees in Defendants with whom a Defendant had an Agreement. The results although different are in line with the damages calculated by the correct regression, demonstrating that the regression is not sensitive to this issue (See line 8 in summary table above).⁸⁴ As I noted above, this is not the correct regression it imposes a specific assumption about impact of the Non-Compete Agreements on mobility (which is impossible to observe).

3. Dr. Lewin Also Attacks the "Total Number of New Hires" Variable

- 133. Dr. Lewin also criticizes my analysis and presents variations on my model. In addition to rehashing Dr. Murphy's and Dr. Stiroh's criticisms, he drops Adobe observations from the regression and observes that the estimated undercompensation increases. He claims this is evidence that the model is misspecified. He then follows in the footsteps of Dr. Stiroh and modifies the total new hires variable by recalculating it to remove Adobe. Dr. Lewin's resulting model then estimates even higher damages. Dr. Lewin interprets this to mean that the conduct was not similarly effective across Defendants and that my model is misspecified.
- 134. Dr. Lewin's "sensitivities" are invalid. Without justification he modifies the data--both regarding the nature of conspiracy and of the amount of hiring. As described above (in regard to Dr. Stiroh's Intel 2006 change), changing the conspiracy data is also not a valid sensitivity analysis. It simply doesn't matter if

⁸⁴ Note that this is not the same as disaggregating the model by Defendant, as Dr. Murphy and Dr. Stiroh have each put forward among their various analyses. As I described in my earlier Class Cert Reply Report and discuss below, disaggregating by employer, the way Dr. Murphy and Dr. Stiroh have, is not appropriate.

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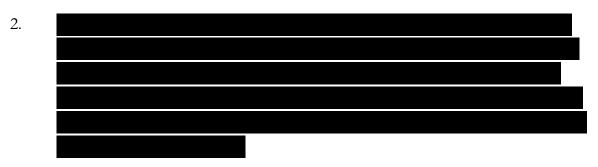
a damage estimate is sensitive to irrelevant perturbations of the model. Also, as I described above, the total new hires variable is not a conspiracy variable and captures important economic factors affecting the Defendants. Dr. Lewin's changes are inappropriate and invalid.

Edward E. Leamer, Ph.D.

December 11, 2013

APPENDIX A. Dr. Becker's Salary Ranges

1. Dr. Becker mischaracterizes the extent of variation in employee compensation as evidence of lack of salary structure. As I described earlier, she provides several examples of employee cohort with seemingly wide salary variations, but makes no effort to investigate the factors that may easily account for that variation.



3. As with Intel, Apple's salary ranges shrink once other factors are taken into account. Dr. Becker identifies the salary range for employees with the title in 2008 to be from about .85

However, this includes employees with tenures ranging from a month to almost 27 years and with ages ranging from 26 to 63. If, for example, you narrow down the population to those employees whose tenure is less than six years and whose ages range from 28 to 31, the salaries for these five employees range from

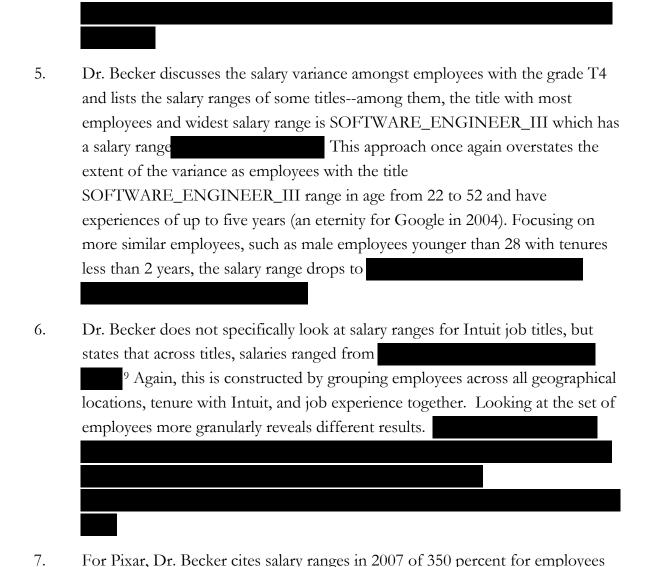
4. Dr. Becker lists a few Adobe job titles as examples of titles with wide ranges but focused on

However, as with the example she cited for Apple,

Once these discrepancies in employee characteristics are considered, salary ranges shrink considerably.

⁸⁵ Becker Report at par. 65-67.

⁸⁶ Becker Report at par. 73-75.



with the title TECHNICAL_DIRECTOR and 135 percent for employees with the title ANIMATOR.⁹⁰ Again, this greatly overstates the situation⁹¹. Female

⁸⁷ Dr. Becker also states that Adobe has seven different salary ranges for job code 3001078, but she neglects to explain that the different ranges are for different geographical areas which have different costs of living. In fact, the salary ranges for the US Bay Area and New York are nearly identical, as are the ranges for Seattle and Boston.

⁸⁸ Becker Report at par. 38, 87 and exhibit A.1.

⁸⁹ Becker Report at par. 89.

⁹⁰ Becker Report at par. 92-93.

TECHNICAL_DIRECTOR employees with ages from 28 to 31 and tenures from 3 to 4 years had salary ranges from \$68,200 to \$70,200. Likewise, the 5 employees in their thirties with the title ANIMATOR and with tenures of 5 to 6 years had salaries that ranged from \$114,000 to \$117,000.

8. Dr. Becker cites the range in salaries for Lucasfilm employees with the job title SOFTWARE_ENGINEER in 2007 as to infer that these wide ranges make it unlikely that compensation would move together. 92 of wide range in salaries by job title. Again, in doing this analysis she does not account for any employee characteristics that may directly affect compensation. For example, for the subset of 2007 employees with the title SOFTWARE_ENGINEER and tenures between 3 and 6 years, salaries ranged from \$80,000 to \$93,000.

⁹¹ Dr. Becker also overstates the range by including Interns that were in the process of transferring to full time employees in her range calculation. By mid 2008, both employees who were making \$40,400 had salary increases to above \$68,000. See PIX00005977_Confidential -- Attorneys' Eyes Only.

⁹² Becker Report at par 97.

Exhibit 1

December 11, 2013

CURRICULUM VITAE

Edward E. Leamer

Position: Chauncey J. Medberry Chair in Management

Professor of Statistics Professor of Economics

Director, Business Forecast Project

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E-Mail: edward.leamer@anderson.ucla.edu

Birth: May 24, 1944

Education: B.A., Princeton, 1966, mathematics

M.A., University of Michigan, mathematics(statistics) Ph.D., University of Michigan, 1970, economics

Honors: Society of Sigma Xi

Fellow, Econometric Society

Fellow, American Academy of Arts and Sciences

New Horizons in Economic Thought, Appraisals of Leading Economists, ed. by Warren J. Samuels, chapter by Herman Leonard and Keith Maskus, 1992.

Graham Lecture, Princeton University, March 1994. Christie Lecture, Millersville University, October 1998.

Who's Who in Economics, edited by Mark Blaug, Edward Elgar

Fathauer Lecture, University of Arizona, 2013

Citibank Teaching Award, 2001

EMBA Teaching Award: 2001, 2002, 2010

Academic Appointments:

Assistant Professor:

Wayne State University, January-June, 1970 Harvard University, July, 1970-June, 1973

Associate Professor:

Harvard University, July, 1973-June, 1975

Professor of Economics:

University of California at Los Angeles, July 1975-

Chauncey J. Medberry Chair in Management:

Anderson Graduate School of Management, July 1990-

Professor of Statistics

University of California at Los Angeles, July 1997-

VITAE EDWARD E LEAMER December 11 2013 page 2

Administrative Positions:

Chairman, Department of Economics:

University of California, Los Angeles, 1983-87.

Area Head, Business Economics:

Anderson Graduate School of Management, 1990-92, 1994-6

Director, UCLA/Anderson Business Forecast, July 2000 -

Visiting Positions:

Visiting Professor:

University of Southern California, 1979-80

University of Basel, June 1990.

Central European University, April 1993.

Graduate School of Business, University of Chicago, Fall 1994

Yale University, 1995

Universidad de San Andreas, Argentina, 1997

University of Oregon, 2001

Gastprofessor:

Institute for Advanced Studies, Vienna, October 1987, June 1991, July 1992, April 1993, June 1995

Visiting Scholar:

Federal Reserve Board, March 1988, September 1989, September 1991, September 1993, May 1996

International Monetary Fund, 1992, 1993.

Lecturer, National Science Council, Republic of China, Dec. 1991.

United States Study Center, University of Sydney, 2009

Visiting Fellowship:

Department of Statistics (Econometrics), The Australian National University, August-September, 1988

Research Fellow:

National Bureau of Economic Research, 1989-.

Lecturer:

Dutch Network for Quantitative Economics, May 1990.

Fellowships, Grants:

NSF graduate traineeship, 1966-67

NDEA Fellowship, 1967-70

National Science Foundation Grant GS31929, Bayesian Inference with Economic Data, U.S. State Department, 1970-71, "Tariffs and the Commodity Composition of Trade," with R.M. Stern, University of Michigan

Federal Reserve, Board of Governors, 1971-72, "Controlling Monetary Aggregates"

Department of Labor, 1974-75, "Tariffs and the Allocation of Labor"

National Science Foundation Grant, SOC 76-08863, 1976-78

Ford Foundation Grant, "The Commodity Composition of Trade," 1977-79

National Science Foundation, SOC 78-09477, 1978-80, "Bayesian Statistical Search and Estimation Procedures'

Department of Labor, "Trade and Employment," 1978-79 National Science Foundation, renewal, 1980-82, 1982-84, 1984-86, 1986-7

World Bank, "Effects of Non-tariff Barriers", 1986-87.

National Science Foundation, "Determinants of the Real Exchange Rate", with Sebastian Edwards, 1986-7

Sloan Foundation, "Empirical Studies of the Effect of U.S. International Economic Policy on the Distribution of Income", 1987-93

National Science Foundation, "Bayesian Elicitation Diagnostics," 1989-91.

Labor Department, "Estimates of the Effects of Non-tariff Barriers", 1989-90.

National Science Foundation, "Economic Integration of High-wage and Low-wage Economies," 1992-4, 1994-96.

Chiang Ching-Kuo Foundation for International Scholarly Exchange, "Economic Integration of Taiwan with Mainland China," with Ivan Pn'g, 1993-4.

Price Waterhouse, "Does U.S. Foreign Direct Investment Reduce Domestic Investment?", 1993-4.

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Professional Activities:

Global Fellow, UCLA, 2004-7

Associate Editor.

Review of Economics and Statistics, 1970-1996

Quarterly Journal of Economics, 1970-75

Journal of the American Statistical Association, 1975-1979

Sage Foundation, "Trade and US Wages," 1997-2000.

Econometrica, 1975-1979

Journal of International Economics, 1988-1994

Econometric Theory, 1985-1988.

Journal of Applied Econometrics, 1985-92

Editorial Board

The Journal of International Trade and Economic Development, 1995-

Asia Pacific Management Review, 2000-

The North American Journal of Economics and Finance, 2005-

economics, 2007-

Co-editor

Journal of International Economics, 1989-93

Editor

Data Point, Harvard Business Review, 2004-5.

Advisory Committee

Handbook of Applied Econometrics

Advisory Board for International Trade Abstracts, 1996-

Referee

Various Journals

Outsider Reviewer

Department of Economics, University of Oregon, May 1995

National Science Foundation Panel for Evaluation of Proposals, 1976-78

Chair, L.J. Savage Memorial Prize Committee, 1979-1981

National Research Council, Committee on Basic Research in the Behavioral and Social Sciences, Working Group on Measurement and Scaling.

Frontiers of Economics, Speaker, World Bank, 1985.

National Science Foundation Panel on Empirical Studies in Economics, December 1987.

Sloan Foundation Fellowship Committee, 1988-93.

Australian Economics Congress, Invited Speaker, August 1988.

Commission on Graduate Education in Economics, American Economic Association.

Panel on Foreign Trade Statistics, National Research Council, National Academy of Sciences.

9th World Congress of the International Economics Association, Invited Speaker.

National Academy of Sciences, Speaker: "Public Policy to Maintain America's Technological Leadership," annual meeting, April 1994.

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Nominating Committee, American Economic Association, 1992-3.

Contingent Valuation Panel, National Oceanographic and Atmospheric Administration, 1992.

Council of Economic Advisors, State of California, 1995-98, 2009-11

Council of Economic Advisors, State Comptroller, 2007-8

Faculty Executive Board, Clausen Center, Haas School of Business, 1996-7

NRER

ITI summer conference organizer, 1999-2000

Bureau of Economic Analysis, Advisory Committee, 2002 –7

Queenscare

Investment Committee, 2005-Board of Directors, 2007-11

National Academy Panel on Outsourcing, Chair, 2004-6

Los Angeles Economy and Jobs Commission, 2006-7

UCLA Extension, Board Member, 2006-

Public Outreach

Testimony at US Trade Deficit Commission of Congress, January 2000 Macarthur Working Group on Networks and Inequality, April 2000

Forecast Speaker, Multiple Locations

Teaching Experience:

Econometrics - Statistics Bayesian Inference - Statistics International Trade Economic Theory Principles of Economics Forecasting

Dissertation: Inference with Non-Experimental Data: A Bayesian View

Publications:

Books:

Quantitative International Economics, with R.M. Stern, Boston: Allyn and Bacon, 1970.

Specification Searches: Ad Hoc Inference with Non Experimental Data, John Wiley and Sons, Inc., 1978. Translated into Spanish and Russian.

Sources of International Comparative Advantage: Theory and Evidence, Boston: MIT Press, 1984.

Behind the Numbers: U.S. Trade in the World Economy, with Robert Baldwin and the Panel on Foreign Trade Statistics, National Research Council, Washington, D.C.: National Academy Press, 1992.

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Sturdy Econometrics: Selected Essays of Edward E. Leamer, Economists of the 20th Century, Hants: Edward Elgar, 1994.

Quiet Pioneering: Robert M. Stern and His International Legacy, edited by Keith E. Maskus, Peter M. Hooper, Edward E. Leamer and J. David Richardson, Ann Arbor: The University of Michigan Press, 1997.

International Economics, Worth Series in Outstanding Contributions, edited by Edward E. Leamer, New York: Worth Publishers, 2001.

Handbook of Econometrics, Vol. 5, edited by James Heckman and Edward Leamer, 2004.

Handbook of Econometrics, Vol. 6A, edited by James Heckman and Edward Leamer, 2007.

Handbook of Econometrics, Vol. 6B, edited by James Heckman and Edward Leamer, 2007.

Macroeconomic Patterns and Stories, Springer-Verlag, 2009.

The Craft of Economics: Lessons from the Heckscher-Ohlin Framework, Ohlin Lecture, M.I.T. Press, 2012.

Tariff and Nontariff Barriers to International Trade, in process.

The Analysis of Data, in process.

NAFTA and Central America, World Bank Monograph, in process.

Who's Afraid of Global Trade?, in process.

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December 11, 2013

Op-Ed Pieces:

- "Privatize Social Security? Here's Why," LA Times, October 2000
- "Cyclically, We're Back to the Past," LA Times, December 4, 2000
- "Is there a Real Estate Bubble?, LA Business Journal, June 27, 2005
- "What Happens When the Housing Market Cools?" LA Business Journal, Jan 15, 2006
- "A Dose of Urgency for Home Buyers," New York Times, April 2008.
- "Let's Stop Paying Wall Street's Gambling Debts," with Larry Kotlikoff, Forbes, April 2008.
- "Running a National Sale," with Larry Kotlikoff, Financial Times, October 2008.
- "An Undergraduate Error," National Journal, December 2008
- "What might tell us when this mess will start getting better?" National Journal, March 2009
- "The US is NOT experiencing a second Great Depression," National Journal, June 2009.
- "What We Need is an AAWP," National Journal, August 2009
- "Dust-up" With Brad DeLong, Los Angeles Times, September 2009

Articles:

"Location Equilibria," **Journal of Regional Science**, Vol, 8 (No. 2, 1968), 229-242, reprinted in A.J. Scott, ed., Location Allocation Systems: A reader (San Francisco: Holden-Day, Inc.), forthcoming.

"Problems in the Theory and Empirical Estimation of International Capital Movements," with R.M. Stern, in F. Machlup, S. Salant and L. Tarshis, eds., **International Mobility and Movement of Capital** (National Bureau of Economic Research, New York), 1972.

"A Class of Informative Priors and Distributed Lag Analysis," **Econometrica**, 40 (November 1972), 1059-81.

"Criteria for Evaluation of Econometric Models," with Phoebus Dhrymes and others, **Annals of Economic and Social Measurement** (July 1972), 259-290.

"False Models and Post-Data Model Construction," **Journal of the American Statistical Association**, 69 (March 1974), 122-131; abstracted in **Zentralblatt fur Mathematik**, reprinted in Omar F. Hamouda and J.C.R. Rowley, **Foundations of Probability, Econometrics and Economic Games**, Edward Elgar Publishing Limited, 1995.

"Empirically-weighted Price and Income Indexes for Import Demand Functions," **Review of Economics and Statistics**, LV (November 1973), 441-450.

"Multicollinearity: A Bayesian Interpretation," **Review of Economics and Statistics**, LV (August 1973), 371-380.

"Nominal Tariff Averages with Estimated Weights," **Southern Economic Journal** (July 1974), 34-46.

"The Commodity Composition of International Trade: An Empirical Analysis," **Oxford Economic Papers**, 26 (November 1974), 350-374.

"A Bayesian Interpretation of Pretesting," with G. Chamberlain, **Journal of the Royal Statistical Society**, Series B, 38 (No. 1, 1976), 85-94.

"Explaining Your results' as Access-Biased Memory," **Journal of the American Statistical Association** (March 1975), 88-83.

"Tariffs in a Trade-Dependence Model," in H. Glejser, ed., **Quantitative Studies of International Economic Relations** (North-Holland Publishing Co., Amsterdam), 1976.

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"Matrix Weighted Averages and Posterior Bounds," with G. Chamberlain, **Journal of the Royal Statistical Society**, Series B, 38 (No. 1 1976), 73-84.

"An Empirical Analysis of the Composition of Manufacturing Employment in the Industrialized Countries," with R.M. Stern and C.F. Baum, **European Economic Review**, 9 (1977), 1-19.

"Regression Selection Strategies and Revealed Priors," **Journal of the American Statistical Association** (September 1978), 580-587.

"Least Squares Versus Instrumental Variables Estimation in a Simple Errors in Variables Model," **Econometrica** (July 1978), 961-968.

"The Information Criterion for the Choice of Regression Models, A Comment," **Econometrica** (March 1979), 507-510.

"Difficulties with Testing for Causation," with R. Jacobs and M. Ward, **Economic Inquiry** (July 1979), 401-13.

"The Leontief Paradox, Reconsidered," **Journal of Political Economy** (June 1980), 495-503; reprinted in J. Bhagwati, ed., **International Trade: Selected Readings**, Cambridge: MIT Press, 1986; reprinted in J. Peter Neary, ed., International Trade: The International Library of Critical Writings in Economics, Edward Elgar, forthcoming, 1994; reprinted in Heinz D. Kruz and Christian Lager, **Input-Output Analysis**, Edward Elgar Publishing Limited, 1997; reprinted in Edward E. Leamer, **International Economics**, Worth Publishers, 2001.

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"Welfare Computations and the Optimal Staging of Tariff Reductions in Models with Adjustment Costs," **Journal of International Economics**, 10 (1980), 21-36.

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"Is It a Supply Curve, or Is It a Demand Curve: Partial Identification through Inequality Constraints," **Review of Economics and Statistics**, Vol. LXIII, No. 3 (August 1981), 319-327.

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"Sets of Posterior Means with Bounded Variance Priors," **Econometrica**, 50 (May 1982), 725-736.

"Comment on `Specification Analysis with Discriminating Priors'," by Thomas F. Cooley, **Econometric Reviews**, First Issue, 1982.

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"Nonexperimental Inference," in S. Kotz and N.L. Johnson, eds., **Encyclopedia of Statistical Sciences**, vol. 6, New York: John Wiley and Sons, 1985.

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"Self Interpretation," **Economics and Philosophy**, (1, 1985), 295-302; abstracted in The Philosopher's Index.

"Econometric Metaphors," in T. Bewley, ed., **Advances in Econometrics, Fifth World Congress**, Cambridge: Cambridge U. Press, 1987.

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December 11, 2013

"Cross Section Estimation of the Effects of Trade Barriers," in R. Feenstra, ed., **Empirical Methods for International Trade**, Cambridge: MIT Press, 1987, 52-82.

"Multi-country Multi-factor Tests of the Factor Abundance Theory," with H.P. Bowen and L. Sveikauskus, **American Economic Review**, 77, no. 5, December 1987, 791 - 809; reprinted in Peter Neary, ed., **International Trade: The International Library of Critical Writings in Economics**, London: Edward Elgar Publishing, Ltd.; reprinted in Edward E. Leamer, **International Economics**, Worth Publishers, 2001; reprinted in Danel M. Bernhofen, **Empirical International Trade**, 2009.

"Empirical Tests of Alternative Models of International Growth," with L. Kotlikoff, in Colin I. Bradford and William H. Branson, eds., **Trade and Structural Change in Pacific Asia**, Chicago: University of Chicago Press, 1987, 227 - 269.

"Paths of Development in the Three-Good n-Factor General Equilibrium Model," **Journal of Political Economy**, Vol. 95, No. 5, October, 1987, 961-999.

"Errors-in-Variables in Linear Systems," Econometrica, Vol. 55, No. 4, July, 1987, 893 -909.

"The Sensitivity of International Comparisons of Capital Stock Measures to Different 'Real Exchange Rates", **American Economic Review, Papers and Proceedings,** May 1988, 78, No. 2, 479 - 483.

"Measures of Openness" in R. Baldwin, ed., **Trade Policy Issues and Empirical Analysis**, University of Chicago Press, 1989, 147-200.

"Causality", discussion papers by Paul W. Holland, in Clifford C.Clogg, ed., **Sociological Methodology**, 1988, 485- 493.

"Things That Bother Me," **Proceedings from the 1988 Australian Economics Congress,** Michael McAleer and Ric Simes, eds., **Economic Record**, 64, (December 1989), 331-335.

"Optimal Aggregation of Linear Net Export Systems," in Terry Barker and M. Hashem Pesaran, eds., **Disaggregation in Econometric Modelling**, London: Routledge, 1990, 150-170.

"Planning, Criticism and Revision," in Michael McAleer, ed., **Topics in Applied Econometrics**, **Journal of Applied Econometrics**, Vol. 4S, (December 1989), S5-S28.

"The Structure and Effects of Tariff and Nontariff Barriers in 1983," in Anne P. Krueger and Ronald Jones, eds. **Festschrift** for Robert Baldwin, Basil Blackwell, 1990, 224-260.

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	Stiroh, Lauren		12/09/13
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	Expert Witness Report of K	evin Murphy	11/13/12
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Exhibit 3 – Original Leamer Model

Observation:Employee ID record in December of each year **Dependant Variable:**Log(Total Annual Compensation/CPI)

Variable Estimate St. Error T. Value (1)			Robust	
1. Conduct * (Log Age - Log(38)) 1. Conduct * (Log Age - Log(38)) 2. Conduct * (Log(Age)* − Log(38)*2) 3. Conduct * (Log(Age)* − Log(38)*2) 3. Conduct * (Log(Age)* − Log(38)*2) 4. Conduct * (Log(Age)* − Log(38)*2) 4. Conduct * (Log(Auper)* − Log(10 − Log(38)*2) 5. ADOBE * Log(Total Annual Compensation/CPI) (-1) 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 7. GOOGLE * Log(Total Annual Compensation/CPI) (-1) 7. GOOGLE * Log(Total Annual Compensation/CPI) (-1) 8. INTIEL * Log(Total Annual Compensation/CPI) (-1) 9. INTULT * Log(Total Annual Compensation/CPI) (-2) 9. Condition * Log(Total Annual Compensation/CPI) (-2) 9. Conditi	Variable	Estimate	St. Error	T-Value
1. Conduct * (Log Age - Log(38)) 2. Conduct * (Log(Age)*2 - Log(38)*2 2. Conduct * (Log(Age)*2 - Log(38)*2 3. Conduct * (Log(Age)*2 - Log(38)*2 3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92) 4. Conduct 4. Conduct 4. Conduct 4. Conduct 5. ADOBIE * Log(Total Annual Compensation/CPI) (-1) 5. ADOBIE * Log(Total Annual Compensation/CPI) (-1) 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 6. RIVILE * Log(Total Annual Compensation/CPI) (-1) 6. LUCASFILM* Log(Total Annual Compensation/CPI) (-1) 6. LUCASFILM* Log(Total Annual Compensation/CPI) (-1) 6. LUCASFILM* Log(Total Annual Compensation/CPI) (-2) 6. ADOBE * Log(Total Annual Compensation/CPI) (-2) 6. ADOBE * Log(Total Annual Compensation/CPI) (-2) 6. COOGLE * Log(Total Annual Compensation/CPI) (-2) 6. RIVILT * Log(Total Annual Compensation/CPI) (-2) 6. RI		(1)	(2)	(3)
2. Conduct * (Log(Age)^2 - Log(38)^2) -0.1586 *** 0.0582 -2.7262 3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92) -0.0170 0.0344 -1.5267 4. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92) -0.0150 0.0044 -1.5267 5. ADOBE ** Log(Total Annual Compensation/CPI) (-1) 0.6738 **** 0.0572 11.8890 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 0.422 **** 0.0720 6.0096 8. INTEL * Log(Total Annual Compensation/CPI) (-1) 0.6818 **** 0.0300 21.3018 9. INTUIT * Log(Total Annual Compensation/CPI) (-1) 0.652 **** 0.0401 13.2931 10. LUCASITLM * Log(Total Annual Compensation/CPI) (-1) 0.6739 **** 0.0802 11.6247 11. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.300**** 0.0455 6.902 12. ADDBE * Log(Total Annual Compensation/CPI) (-2) 0.306*** 0.0405 6.0597 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.36*** 0.0415 6.0597 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.36*** 0.0447 6.8204 17. LUC				(1)/(2)
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92) -0.0170 0.0344 -0.5607 4. Conduct -0.0559 0.0447 -1.2505 5. ADOBE * Log(Total Annual Compensation/CPI) (-1) 0.0738 *** 0.0567 11.8890 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 0.4329 *** 0.0579 12.5919 7. GOOGLE * Log(Total Annual Compensation/CPI) (-1) 0.6818 *** 0.0320 21.3018 8. NTEL * Log(Total Annual Compensation/CPI) (-1) 0.6827 *** 0.0491 13.2931 9. NTUIT * Log(Total Annual Compensation/CPI) (-1) 0.932 *** 0.0401 13.2931 10. LUCASFILM* * Log(Total Annual Compensation/CPI) (-2) 0.3002 *** 0.0467 4.5952 12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.2456 *** 0.0445 6.0597 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.2456 *** 0.0416 6.0597 14. Eng(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.1772 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.372 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.	1. Conduct * (Log Age - Log(38))	1.1741 ***	0.4417	2.6583
4. Conduct -0.0559 0.047 -1.2505 5. ADOBE* Log(Total Annual Compensation/CPI) (-1) 0.6738*** 0.0567 11.8890 6. APPLE** Log(Total Annual Compensation/CPI) (-1) 0.7289*** 0.0790 16.096 7. GOGGLE** Log(Total Annual Compensation/CPI) (-1) 0.6812**** 0.0720 6.096 8. INTELT** Log(Total Annual Compensation/CPI) (-1) 0.682**** 0.0491 13.2931 10. LUCASFILM ** Log(Total Annual Compensation/CPI) (-1) 0.9327*** 0.0802 11.6247 11. PIXAR ** Log(Total Annual Compensation/CPI) (-2) 0.3002*** 0.0032 1.6248 12. ADOBE ** Log(Total Annual Compensation/CPI) (-2) 0.3002*** 0.0455 6.0908 13. APPLE** Log(Total Annual Compensation/CPI) (-2) 0.366**** 0.0455 6.0908 13. APPLE** Log(Total Annual Compensation/CPI) (-2) 0.366***** 0.0945 6.0907 14. GOOGLE** Log(Total Annual Compensation/CPI) (-2) 0.368**** 0.0944 1.0214 15. In STEL*** Log(Total Annual Compensation/CPI) (-2) 0.368**** 0.0944 1.0224 16. In VILUT** Log(Total Annual Compensation/CPI) (-2) 0.0432 0	2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1586 ***	0.0582	-2.7262
5 ADOBE * Log(Total Annual Compensation/CPI) (-1) 0.6738 *** 0.0567 11.8890 6. APPLE * Log(Total Annual Compensation/CPI) (-1) 0.7289 *** 0.0579 12.5919 7. GOOGLE* Log(Total Annual Compensation/CPI) (-1) 0.6329 *** 0.0300 21.3018 8. INTLIT * Log(Total Annual Compensation/CPI) (-1) 0.6681 *** 0.0300 21.3018 9. INTLIT * Log(Total Annual Compensation/CPI) (-1) 0.9527 *** 0.0491 1.32931 10. LUCASPILM* * Log(Total Annual Compensation/CPI) (-1) 0.9527 *** 0.0405 6.9008 13. APPLE* * Log(Total Annual Compensation/CPI) (-2) 0.3002 *** 0.0435 6.9008 13. APPLE* * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0415 7.1772 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.1772 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.345 *** 0.0514 7.1772 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 15. INTEL* * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 16. INTUIT * Log(Total Annual Compensation/CPI) (-	3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0170	0.0304	-0.5607
6. APPLE * Log(Total Annual Compensation/CPI) (-1) 0.7289*** 0.0579 1.25919 7. GOOGLE * Log(Total Annual Compensation/CPI) (-1) 0.4329*** 0.070 6.009 8. NTEL* * Log(Total Annual Compensation/CPI) (-1) 0.6527*** 0.0401 13.2931 19. NTUIT* * Log(Total Annual Compensation/CPI) (-1) 0.9327*** 0.0402 11.6247 11. PIXAR* * Log(Total Annual Compensation/CPI) (-2) 0.3002*** 0.0455 6.0008 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456*** 0.0405 6.0001 14. GOOGLE* * Log(Total Annual Compensation/CPI) (-2) 0.2456*** 0.0405 6.0001 14. GOOGLE* * Log(Total Annual Compensation/CPI) (-2) 0.3045*** 0.041 7.1772 15. INTUI* * Log(Total Annual Compensation/CPI) (-2) 0.3045** 0.007 8.0248 16. INTUIT* * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.041 0.007 8.224 17. LUCASFILM* * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.041 0.016 0.004 8.004 9.004 1.016 0.004 0.004 0.004 0.004 0.004 0.004 0.004 0.004 0.004 0.004 0.004	4. Conduct	-0.0559	0.0447	-1.2505
7. GOGGLE * Log(Total Annual Compensation/CPI) (-1) 0.4329 *** 0.0720 6.0006 8. INTEL * Log(Total Annual Compensation/CPI) (-1) 0.6818 *** 0.0320 21.3018 9. INTUIT * Log(Total Annual Compensation/CPI) (-1) 0.0527 *** 0.0491 13.2931 10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1) 0.0737 *** 0.1467 4.5952 12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.0302 *** 0.0435 6.0907 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456 *** 0.005 6.0507 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.051 7.172 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.051 7.172 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.3045 *** 0.0078 10.2218 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0345 *** 0.041 0.0818 0.5286 18. PIXAR* * Log(Total Annual Compensation/CPI) (-2) 0.0345 *** 0.041 0.0818 0.5286 19. Log(Age) (Years) 0.0562 *** 0.177 -3.3191 0.041 0.041 0.0868 0.0868 0.041 0.0868 0.041	5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6738 ***	0.0567	11.8890
8. INTEL * Log(Total Annual Compensation/CPI) (-1) 0.6818 *** 0.0320 2.13018 9. INTUIT* Log(Total Annual Compensation/CPI) (-1) 0.6527 *** 0.091 13.2931 10. IUCASFILM* Log(Total Annual Compensation/CPI) (-1) 0.6739 *** 0.0802 11.6247 11. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.3002 *** 0.0435 6.9098 12. ADDBE * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0014 7.172 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.172 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.172 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.808 19. Log(Age) (Years) 0.0662 *** 0.1977 3.3191 20. Log(Age) (Years) 0.0790 *** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.0472 22. Log(Company Tenure) (Months) 0.018 0.0471	6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7289 ***	0.0579	12.5919
9. INTUIT* Log(Total Annual Compensation/CPI) (-1) 0.6527*** 0.0491 13.2931 10. LUCASFILM* Log(Total Annual Compensation/CPI) (-1) 0.9527*** 0.0802 11.6247 11. PIXAR* Log(Total Annual Compensation/CPI) (-2) 0.6739*** 0.0435 6.908 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456*** 0.0405 6.0597 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3687*** 0.0514 7.1772 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.3045*** 0.0447 6.8204 16. INTUIT* * Log(Total Annual Compensation/CPI) (-2) 0.3045*** 0.0447 6.8204 16. INTUIT* * Log(Total Annual Compensation/CPI) (-2) 0.0345*** 0.0447 6.8204 16. INTUIT* * Log(Total Annual Compensation/CPI) (-2) 0.0345*** 0.0447 6.8204 17. LUCASFILM* * Log(Total Annual Compensation/CPI) (-2) 0.0431 0.0116 0.808 19. Log(Age)* (Years) 0.0941 0.1166 0.808 19. Log(Age)* (Years) 0.0094 0.0125 3.1301 20. Log(Company Tenure)* (Months) 0.018 0.041 0.014 21. Log(Company Tenure)* (Months) 0.018 0.002	7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4329 ***	0.0720	6.0096
10. LUCASFILM* Log(Total Annual Compensation/CPI) (-1) 0.9327*** 0.0802 11.6247 11. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.6739*** 0.1467 4.5956 12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.3002*** 0.0435 6.9098 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456*** 0.0405 6.0597 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3087*** 0.0147 6.8204 15. INTEL* * Log(Total Annual Compensation/CPI) (-2) 0.3045*** 0.0447 6.8204 17. LUCASFILM* * Log(Total Annual Compensation/CPI) (-2) 0.0345*** 0.0447 6.8204 17. LUCASFILM* * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age)* (2 0.0990** 0.0252 3.1301 21. Log(Corpany Tenure)* (Months) 0.018 0.0451 0.4172 22. Log(Company Tenure)* (Months) 0.0013 0.0047 0.0262 23. Male 0.0057 *** 0.0026 2.2267 24. Diog(Information Sector Employment in San-Jose) 1.872** 0.4717 <td< td=""><td>8. INTEL * Log(Total Annual Compensation/CPI) (-1)</td><td>0.6818 ***</td><td>0.0320</td><td>21.3018</td></td<>	8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6818 ***	0.0320	21.3018
11. PIXAR * Log(Total Annual Compensation/CPI) (-1) 0.6739 **** 0.1467 4.5952 12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.3002 **** 0.0455 6.0908 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456 **** 0.0451 7.1772 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.1772 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2841 *** 0.0278 10.2218 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 19. Luc/Scyl (Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.0562 *** 0.1977 -3.3191 20. Log(Age) (Years) 0.0790 *** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure) (Months) 0.0013 0.0047 -0.2829 23. Male 0.0003 0.0013 0.0047 0.2262 24. DLog(Information Sector Employment in San-Jose) 1.8727 *** 0.0717 3.970	9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6527 ***	0.0491	13.2931
12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.3002 *** 0.0435 6.9080 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456 *** 0.0405 6.0597 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.1772 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2841 *** 0.0278 10.2218 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.808 18. PEXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.808 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.3191 20. Log(Age) (Years) -0.0562 *** 0.1977 -3.3191 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure) (Months) 0.0013 0.0047 -0.282 23. Male 0.0057 ** 0.0026 2.2267 24. Dlog(Information Sector Employment in San-Jose) 1.8727 *** 0.4717 3.9703 25. Log(Total Number of Tensfers Among Defendants) 0.0041 0.003 0.0436	10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9327 ***	0.0802	11.6247
13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2456*** 0.0405 6.0597 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3687*** 0.0514 7.1772 15. INTEL* * Log(Total Annual Compensation/CPI) (-2) 0.3045*** 0.0447 6.8204 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8086 19. Log(Age) (Years) 0.0562*** 0.197 -3.3191 20. Log(Age) (Years) 0.0018 0.0451 0.1166 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure) (Years) 0.0013 0.0041 0.0252 3.1301 23. Male 0.0057** 0.0026 2.2267 24. DLog(Information Sector Employment in San-Jose) 1.8727*** 0.471 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029*** 0.081 2.7025 26. Year (trend) 0.0265 0.0267 0.0920 27. Log(Number of New Hires) In the Firm/Number of Employees(-1) 0.0265 0.0267 0.0920 28. Log(To	11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6739 ***	0.1467	4.5952
14. GOOGLE *Log(Total Annual Compensation/CPI) (-2) 0.3687 *** 0.0514 7.1772 15. INTEL *Log(Total Annual Compensation/CPI) (-2) 0.2841 *** 0.0278 10.2218 16. INTUITY *Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 17. LUCASFILM *Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 18. PIXAR *Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.3191 20. Log(Age) (Years) 0.0709 *** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.047 22. Log(Company Tenure) ** 0.0013 0.0047 -0.282 23. Male 0.0057 ** 0.0026 2.2267 24. DLog(Information Sector Employment in San-Jose) 1.872**** 0.471 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires) In the Firm/Number of Employees(-I)) 0.0265 0.0267 0.9920 28. Log(Firm Revenue Per E	12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3002 ***	0.0435	6.9008
15. INTEL* Log(Total Annual Compensation/CPI) (-2) 0.2841 **** 0.0278 10.218 16. INTUIT* Log(Total Annual Compensation/CPI) (-2) 0.3045 *** 0.0447 6.8204 17. LUCASFILM* Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.3191 20. Log(Capp) (Years) 0.0790 *** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure) (Months) 0.0013 0.0047 -0.2829 23. Male 0.0057 ** 0.0026 2.2267 24. DLog(Information Sector Employment in San-Jose) 1.8727 **** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.0381 2.7025 26. Year (trend) 0.0041 0.003 -0.4920 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Firm Revenue Per Employee/CPI) (-1) 0.034 0.0752 1.8909 31. APPLE 0	13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2456 ***	0.0405	6.0597
16. INTUIT* Log(Total Annual Compensation/CPI) (-2) 0.3045 *** 0.0447 6.8204 17. LUCASPELM* Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.319 20. Log(Age)^2 0.0790 *** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure) Tenure) 0.0057 ** 0.0026 2.2267 23. Male 0.0057 ** 0.006 2.2267 24. DLog(Information Sector Employment in San-Jose) 1.8727 *** 0.071 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.0381 2.7025 26. Year (trend) 0.0041 0.0083 0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.992 28. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.0346 *** 0.0752 1.8096 31. APPLE 0.063	14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3687 ***	0.0514	7.1772
17. LUCASFILM* Log(Total Annual Compensation/CPI) (-2) 0.0432 0.0818 0.5286 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.3191 20. Log(Age)^2 0.0790 *** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure) P2 -0.0013 0.0047 -0.2829 24. Dlog(Information Sector Employment in San-Jose) 1.8727 *** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.033 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346 *** 0.0092 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. Dog(Firm Revenue Per Employee/CPI) (-1) 0.0853 0.2582 0.3304 31. APTE 0.0853 0.2582 0.3304 32. LOG(SELLA) 0.0863 0.2582	15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2841 ***	0.0278	10.2218
18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.3191 20. Log(Age) (Years) 0.0790 **** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.01188 0.0451 0.4122 22. Log(Company Tenure) ^2 -0.0013 0.0047 -0.2829 23. Male 0.0057 ** 0.0026 2.2267 24. Dlog(Information Sector Employment in San-Jose) 1.8727 *** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346 *** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. Dlog(Firm Revenue Per Employee/CPI) (-1) 0.0853 0.2582 0.3304 31. APPLE 0.0653 0.2582 0.3304 32. GOOGLE 1.3198 *** 0.4365 3.0239	16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3045 ***	0.0447	6.8204
18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0941 0.1166 0.8068 19. Log(Age) (Years) -0.6562 *** 0.1977 -3.3191 20. Log(Age) (Years) 0.0790 **** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.01188 0.0451 0.4122 22. Log(Company Tenure) ^2 -0.0013 0.0047 -0.2829 23. Male 0.0057 ** 0.0026 2.2267 24. Dlog(Information Sector Employment in San-Jose) 1.8727 *** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346 *** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. Dlog(Firm Revenue Per Employee/CPI) (-1) 0.0853 0.2582 0.3304 31. APPLE 0.0653 0.2582 0.3304 32. GOOGLE 1.3198 *** 0.4365 3.0239	17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0432	0.0818	0.5286
20. Log(Age)**2 0.0790**** 0.0252 3.1301 21. Log(Company Tenure) (Months) 0.0188 0.0451 0.4172 22. Log(Company Tenure)**2 -0.0013 0.0047 -0.2829 24. Dlog(Information Sector Employment in San-Jose) 1.872**** 0.471 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029*** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346**** 0.0092 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.0853 0.2582 0.3304 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198*** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2487 34. INTUIT 0.0891 0.2179 0.4867 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** <td< td=""><td></td><td>0.0941</td><td>0.1166</td><td>0.8068</td></td<>		0.0941	0.1166	0.8068
21. Log(Company Tenure) (Months)	19. Log(Age) (Years)	-0.6562 ***	0.1977	-3.3191
22. Log(Company Tenure)^2 -0.0013 0.0047 -0.2829 23. Male 0.0057 ** 0.0026 2.2267 24. DLog(Information Sector Employment in San-Jose) 1.8727 **** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 **** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346 **** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198 *** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES	20. Log(Age)^2	0.0790 ***	0.0252	3.1301
23. Male 0.0057 ** 0.0026 2.2267 24. DLog(Information Sector Employment in San-Jose) 1.8727 **** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 **** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346 *** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3349 32. GOOGLE 1.3198 *** 0.4365 3.0234 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES R-Square 0.0868	21. Log(Company Tenure) (Months)	0.0188	0.0451	0.4172
24. DLog(Information Sector Employment in San-Jose) 1.8727 *** 0.4717 3.9703 25. Log(Total Number of Transfers Among Defendants) 0.1029 *** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346 *** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.0853 0.2582 0.3304 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198 *** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES R-Square 0.0868	22. Log(Company Tenure)^2	-0.0013	0.0047	-0.2829
25. Log(Total Number of Transfers Among Defendants) 0.1029*** 0.0381 2.7025 26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346*** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198*** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	23. Male	0.0057 **	0.0026	2.2267
26. Year (trend) -0.0041 0.0083 -0.4936 27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346*** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198*** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	24. DLog(Information Sector Employment in San-Jose)	1.8727 ***	0.4717	3.9703
27. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0265 0.0267 0.9920 28. Log(Total Number of New Hires) -0.3346*** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198*** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	25. Log(Total Number of Transfers Among Defendants)	0.1029 ***	0.0381	2.7025
28. Log(Total Number of New Hires) -0.3346*** 0.0692 -4.8358 29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198*** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	26. Year (trend)	-0.0041	0.0083	-0.4936
29. Log(Firm Revenue Per Employee/CPI) (-1) -0.0474 0.0713 -0.6644 30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198 *** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0265	0.0267	0.9920
30. DLog(Firm Revenue Per Employee/CPI) (-1) 0.1360 * 0.0752 1.8090 31. APPLE 0.0853 0.2582 0.3304 32. GOOGLE 1.3198 *** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	28. Log(Total Number of New Hires)	-0.3346 ***	0.0692	-4.8358
31. APPLE 0.0853 0.2582 0.304 32. GOOGLE 1.3198*** 0.4365 3.0239 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	29. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0474	0.0713	-0.6644
32. GOOGLE 1.3198*** 0.4365 3.0299 33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	30. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1360 *	0.0752	1.8090
33. INTEL 0.0634 0.2701 0.2349 34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399*** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	31. APPLE	0.0853	0.2582	0.3304
34. INTUIT 0.0891 0.2179 0.4087 35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	32. GOOGLE	1.3198 ***	0.4365	3.0239
35. LUCASFILM 0.0164 0.2903 0.0566 36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	33. INTEL	0.0634	0.2701	0.2349
36. PIXAR 1.3399 *** 0.3896 3.4393 37. Location (State) Indicators YES 38. Constant R-Square YES 0.868 0.868	34. INTUIT	0.0891	0.2179	0.4087
37. Location (State) Indicators YES 38. Constant YES R-Square 0.868	35. LUCASFILM	0.0164	0.2903	0.0566
38. Constant YES R-Square 0.868	36. PIXAR	1.3399 ***	0.3896	3.4393
R-Square 0.868	37. Location (State) Indicators	YES		
1	38. Constant	YES		
1	R-Square	0.868		
Observations 277,002	Observations	277,082		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 4 - Model with Growth in S&P 500 Index

Observation: Employee ID record in December of each year Dependant Variable: Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1739 ***	0.4414	2.6598
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1586 ***	0.0581	-2.7281
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0171	0.0300	-0.5692
4. Conduct	-0.0569	0.0526	-1.0817
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6736 ***	0.0575	11.7083
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7290 ***	0.0579	12.5927
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4329 ***	0.0726	5.9663
8. INTEL* Log(Total Annual Compensation/CPI) (-1)	0.6815 ***	0.0323	21.0976
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6524 ***	0.0496	13.1536
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9335 ***	0.0854	10.9292
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6740 ***	0.1464	4.6048
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3003 ***	0.0445	6.7445
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2455 ***	0.0405	6.0639
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3686 ***	0.0510	7.2344
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2844 ***	0.0278	10.2361
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3049 ***	0.0454	6.7204
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0422	0.0882	0.4785
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0940	0.1162	0.8085
19. Log(Age) (Years)	-0.6565 ***	0.1989	-3.3008
20. Log(Age)^2	0.0791 ***	0.0254	3.1107
21. Log(Company Tenure) (Months)	0.0185	0.0439	0.4205
22. Log(Company Tenure)^2	-0.0013	0.0046	-0.2835
23. Male	0.0057 **	0.0025	2.2576
24. DLog(Information Sector Employment in San-Jose)	1.8757 ***	0.4969	3.7746
25. Log(Total Number of Transfers Among Defendants)	0.1034 **	0.0445	2.3221
26. Year (trend)	-0.0044	0.0111	-0.3935
27. DLog(S&P 500 Index/CPI)	-0.0030	0.0964	-0.0311
28. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0262	0.0281	0.9345
29. Log(Total Number of New Hires)	-0.3343 ***	0.0663	-5.0428
30. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0477	0.0737	-0.6467
31. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1358 *	0.0733	1.8543
32. APPLE	0.0856	0.2583	0.3313
33. GOOGLE	1.3201 ***	0.4306	3.0656
34. INTEL	0.0633	0.2701	0.2342
35. INTUIT	0.0888	0.2187	0.4060
36. LUCASFILM	0.0183	0.2932	0.0623
37. PIXAR	1.3405 ***	0.3911	3.4279
38. Location (State) Indicators	YES		
39. Constant	YES		
R-Square	0.868		
Observations	277,082		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of
- employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 5 – Model with Market Software Occupation Salaries

Observation:Employee ID record in December of each year Dependant Variable:Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1625 ***	0.4488	2.5900
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1570 ***	0.0591	-2.6573
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0168	0.0307	-0.5465
4. Conduct	-0.0761	0.0582	-1.3080
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6742 ***	0.0566	11.9222
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7289 ***	0.0577	12.6263
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4330 ***	0.0732	5.9109
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6874 ***	0.0344	19.9957
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6544 ***	0.0503	13.0092
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9367 ***	0.0833	11.2436
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6688 ***	0.1463	4.5719
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.2997 ***	0.0439	6.8263
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2455 ***	0.0401	6.1199
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3684 ***	0.0496	7.4296
15. INTEL* Log(Total Annual Compensation/CPI) (-2)	0.2785 ***	0.0265	10.4919
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3034 ***	0.0461	6.5758
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0379	0.0856	0.4433
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0980	0.1160	0.8442
19. Log(Age) (Years)	-0.6516 ***	0.1983	-3.2861
20. Log(Age)^2	0.0784 ***	0.0253	3.1008
21. Log(Company Tenure) (Months)	0.0197	0.0440	0.4468
22. Log(Company Tenure)^2	-0.0014	0.0046	-0.3103
23. Male	0.0057 **	0.0025	2.2943
24. DLog(Information Sector Employment in San-Jose)	1.9731 ***	0.5128	3.8476
25. Log(Total Number of Transfers Among Defendants)	0.1280 **	0.0588	2.1760
26. Year (trend)	-0.0028	0.0099	-0.2888
27. Log(Market Salary for Software Engineers/CPI)	-1.2133	2.3528	-0.5157
28. DLog(Market Salary for Software Engineers/CPI)	0.1138	1.5506	0.0734
29. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0278	0.0270	1.0304
30. Log(Total Number of New Hires)	-0.3827 ***	0.1195	-3.2016
31. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0475	0.0782	-0.6081
32. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1390 *	0.0768	1.8093
33. APPLE	0.0839	0.2584	0.3247
34. GOOGLE	1.3195 ***	0.4280	3.0833
35. INTEL	0.0637	0.2710	0.2351
36. INTUIT	0.0809	0.2173	0.3724
37. LUCASFILM	0.0260	0.2956	0.0878
38. PIXAR	1.3513 ***	0.3957	3.4149
39. Location (State) Indicators	YES	0.5751	5.1177
40. Constant	YES		
R-Square	0.868		
Observations	277,082		
Observations	211,002		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.
- (7) Market Salaries from BLS for four Occupation Categories Computer and Information Research Scientists; Computer Programmers; Software Developers, Applications; Software Developers, Systems Software

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings; BLS

Exhibit 6 - Model with Control Variable for Title Change from Previous Year

Observation: Employee ID record in December of each year Dependant Variable: Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3) (1)/(2)
1. Conduct * (Log Age - Log(38))	1.1793 ***	0.4434	2.6596
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1590 ***	0.0585	-2.7196
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0172	0.0303	-0.5669
4. Conduct	-0.0580	0.0444	-1.3078
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6699 ***	0.0561	11.9372
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7271 ***	0.0580	12.5399
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4373 ***	0.0732	5.9733
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6851 ***	0.0324	21.1455
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6583 ***	0.0460	14.3103
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9156 ***	0.0757	12.0988
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6712 ***	0.1469	4.5691
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3035 ***	0.0422	7.1932
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2470 ***	0.0405	6.1006
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3668 ***	0.0516	7.1076
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2820 ***	0.0275	10.2610
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.2996 ***	0.0406	7.3692
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0603	0.0786	0.7678
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0925	0.1168	0.7918
19. Log(Age) (Years)	-0.5856 ***	0.1917	-3.0552
20. Log(Age)^2	0.0713 ***	0.0246	2.8966
21. Log(Company Tenure) (Months)	0.0142	0.0457	0.3112
22. Log(Company Tenure)^2	-0.0007	0.0047	-0.1548
23. Male	0.0057 **	0.0025	2.3058
24. Indicator for Title Change from Previous Year	0.0565 ***	0.0077	7.3243
25. DLog(Information Sector Employment in San-Jose)	1.9406 ***	0.4654	4.1694
26. Log(Total Number of Transfers Among Defendants)	0.1030 ***	0.0381	2.7025
27. Year (trend)	-0.0029	0.0084	-0.3468
29. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0247	0.0271	0.9113
30. Log(Total Number of New Hires)	-0.3490 ***	0.0692	-5.0437
31. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0360	0.0701	-0.5137
32. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1285 *	0.0742	1.7326
33. APPLE	0.0738	0.2605	0.2834
34. GOOGLE	1.2852 ***	0.4448	2.8894
35. INTEL	0.0472	0.2740	0.1723
36. INTUIT	0.0801	0.2195	0.3648
37. LUCASFILM	0.0035	0.2940	0.0120
38. PIXAR	1.3771 ***	0.3913	3.5194
39. Location (State) Indicators	YES		
40. Constant	YES		
R-Square	0.871		
Observations	277,082		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.

 $Source: Defendants'\ employee\ compensation\ data; St.\ Louis\ Fed\ Reserve; SEC\ Filings$

December 11, 2013

Exhibit 7 - Model with One Lag of Compensation and Same Title as Previous Year

Observation:Employee ID record in December of each year for employees on the same title two years in a row **Dependant Variable:**Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3)
			(1)/(2)
1. Conduct * (Log Age - Log(38))	0.6534	0.8791	0.7432
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.0872	0.1153	-0.7564
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0422	0.0369	-1.1457
4. Conduct	-0.0846	0.0519	-1.6291
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.9119 ***	0.0343	26.5897
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.8695 ***	0.0327	26.6101
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.6002 ***	0.0556	10.8029
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.9276 ***	0.0266	34.8294
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.9131 ***	0.0169	54.1007
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9445 ***	0.0310	30.5002
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6281 ***	0.0906	6.9350
12. Log(Age) (Years)	0.7044 *	0.3955	1.7808
13. Log(Age)^2	-0.0926 *	0.0517	-1.7913
14. Log(Company Tenure) (Months)	0.1909 *	0.1134	1.6831
15. Log(Company Tenure)^2	-0.0200	0.0126	-1.5929
16. Male	0.0118 ***	0.0036	3.2804
17. DLog(Information Sector Employment in San-Jose)	1.8813 ***	0.6568	2.8644
18. Log(Total Number of Transfers Among Defendants)	0.0694	0.0474	1.4640
19. Year (trend)	-0.0019	0.0112	-0.1683
20. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0310	0.0325	0.9522
21. Log(Total Number of New Hires)	-0.3054 ***	0.0889	-3.4351
22. Log(Firm Revenue Per Employee/CPI) (-1)	0.0072	0.0799	0.0901
23. DLog(Firm Revenue Per Employee/CPI) (-1)	0.0512	0.0764	0.6711
24. APPLE	0.3023	0.3194	0.9464
25. GOOGLE	2.1687 ***	0.4046	5.3604
26. INTEL	-0.0867	0.2741	-0.3162
27. INTUIT	-0.0023	0.2434	-0.0094
28. LUCASFILM	-0.2239	0.3342	-0.6699
29. PIXAR	1.8790 ***	0.6273	2.9954
30. Location (State) Indicators	YES		
31. Constant	YES		
R-Square	0.827		
Observations	235,562		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

December 11, 2013

Exhibit 8 - Model with Bilateral Conduct Variable

Observation:Employee ID record in December of each year **Dependant Variable:**Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
- -	(1)	(2)	(3) (1)/(2)
1. Bilateral Conduct * (Log Age - Log(38))	2.0602 *	1.0762	1.9144
2. Bilateral Conduct * (Log(Age)^2 - Log(38)^2)	-0.2835 *	0.1473	-1.9255
3. Bilateral Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1	-0.0389	0.0542	-0.7183
4. Bilateral Conduct	-0.1363	0.0845	-1.6129
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6535 ***	0.0549	11.9095
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7289 ***	0.0615	11.8544
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4211 ***	0.0677	6.2191
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6827 ***	0.0327	20.9051
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6490 ***	0.0463	14.0231
10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9041 ***	0.0691	13.0765
11. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6701 ***	0.1417	4.7287
12. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3210 ***	0.0381	8.4274
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2504 ***	0.0437	5.7279
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3762 ***	0.0502	7.4997
15. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2840 ***	0.0287	9.9054
16. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3068 ***	0.0420	7.3048
17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0846	0.0743	1.1378
18. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0929	0.1114	0.8336
19. Log(Age) (Years)	-0.5223 ***	0.1847	-2.8280
20. Log(Age)^2	0.0614 ***	0.0240	2.5595
21. Log(Company Tenure) (Months)	-0.0013	0.0382	-0.0351
22. Log(Company Tenure)^2	0.0008	0.0039	0.2065
23. Male	0.0058 **	0.0026	2.2498
24. DLog(Information Sector Employment in San-Jose)	1.9526 ***	0.4354	4.4844
25. Log(Total Number of Transfers Among Defendants)	0.0937 ***	0.0313	2.9918
26. Year (trend)	-0.0008	0.0065	-0.1152
27. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0290	0.0243	1.1907
28. Log(Total Number of New Hires)	-0.3429 ***	0.0652	-5.2628
29. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0626	0.0682	-0.9177
30. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1329 *	0.0711	1.8687
31. APPLE	0.0719	0.2609	0.2755
32. GOOGLE	1.4060 ***	0.4844	2.9024
33. INTEL	0.0779	0.2726	0.2856
34. INTUIT	0.1073	0.2158	0.4970
35. LUCASFILM	-0.0608	0.2886	-0.2107
36. PIXAR	1.3585 ***	0.3666	3.7059
37. Location (State) Indicators	YES		
38. Constant	YES		
R-Square	0.869		
Observations	277,082		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) Standard Errors adjusted for clustering at employer-year level.
- (7) Bilateral conduct variable is defined as the share of technical class employee-years of firms that have an agreement with the defendant as a percent of total class (excluding the defendant).

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

HIGHLY CONFIDENTIAL SUBJECT TO PROTECTIVE ORDER

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Exhibit 9 - Model with Conduct Effects for California State

Observation:Employee ID record in December of each year **Dependant Variable:**Log(Total Annual Compensation/CPI)

		Robust	
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3)
			(1)/(2)
1. Conduct * (Log Age - Log(38))	1.1724 ***	0.4442	2.6393
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1583 ***	0.0585	-2.7071
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0161	0.0311	-0.5189
4. Conduct	-0.0537	0.0468	-1.1485
5. Conduct * (Location State = California)	-0.0032	0.0098	-0.3297
6. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6739 ***	0.0567	11.8766
7. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7289 ***	0.0578	12.6062
8. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4330 ***	0.0721	6.0070
9. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6819 ***	0.0321	21.2652
10. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6522 ***	0.0491	13.2888
11. LUCASFILM * Log(Total Annual Compensation/CPI) (-1)	0.9336 ***	0.0806	11.5774
12. PIXAR * Log(Total Annual Compensation/CPI) (-1)	0.6739 ***	0.1467	4.5930
13. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3000 ***	0.0435	6.8999
14. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2455 ***	0.0404	6.0707
15. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3685 ***	0.0513	7.1810
16. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2840 ***	0.0278	10.2212
17. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3048 ***	0.0447	6.8186
18. LUCASFILM * Log(Total Annual Compensation/CPI) (-2)	0.0421	0.0821	0.5123
19. PIXAR * Log(Total Annual Compensation/CPI) (-2)	0.0942	0.1167	0.8066
20. Log(Age) (Years)	-0.6554 ***	0.1975	-3.3187
21. Log(Age)^2	0.0789 ***	0.0252	3.1283
22. Log(Company Tenure) (Months)	0.0187	0.0452	0.4143
23. Log(Company Tenure)^2	-0.0013	0.0047	-0.2797
24. <u>Male</u>	0.0057 **	0.0026	2.2240
25. DLog(Information Sector Employment in San-Jose)	1.8781 ***	0.4737	3.9648
26. Log(Total Number of Transfers Among Defendants)	0.1029 ***	0.0380	2.7115
27. Year (trend)	-0.0041	0.0083	-0.4949
28. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0261	0.0267	0.9796
29. Log(Total Number of New Hires)	-0.3350 ***	0.0692	-4.8383
30. Log(Firm Revenue Per Employee/CPI) (-1)	-0.0477	0.0716	-0.6656
31. DLog(Firm Revenue Per Employee/CPI) (-1)	0.1362 *	0.0752	1.8102
32. APPLE	0.0857	0.2587	0.3313
33. GOOGLE	1.3200 ***	0.4363	3.0255
34. INTEL	0.0634	0.2702	0.2345
35. INTUIT	0.0904	0.2182	0.4142
36. LUCASFILM	0.0182	0.2907	0.0625
37. <u>PIXAR</u>	1.3393 ***	0.3900	3.4338
38. Location (State) Indicators	YES		
39. Constant	YES		
R-Square	0.868		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December),
- overtime pay, bonus, and value of equity compensation granted.

Observations

- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- $\ensuremath{\text{(6)}}\ Standard\ Errors\ adjusted\ for\ clustering\ at\ employer-year\ level}.$

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

277,082

Exhibit 10 - Model with Hardware Employment Variable for Intel

Observation: Employee ID record in December of each year Dependant Variable: Log(Total Annual Compensation/CPI)

Variable Estimate St. Error TV-Value (1)	Variable		Robust		
1. Conduct * (Log Age * Log(38)) 1. Conduct * (Log Age * Log(38)) 2. Conduct * (Log(Age)*) 2- Log(S8)*2) 2. Conduct * (Log(Age)*) 2- Log(S8)*2) 3. Conduct * (Log(Age)*) 2- Log(S8)*2) 4. Conduct * (Log(Age)*) 4- Log(Dog(Mulber of New Hires In the Firm/Number of Employees(·II) + 1.92) 4. Conduct 4. Conduct 5. ADOBE * Log(Total Annual Compensation/CPI) (·I) 6. APPLE * Log(Total Annual Compensation/CPI) (·I) 6. RNTEL * Log(Total Annual Compensation/CPI) (·I) 6. LUCASPILIA* * Log(Total Annual Compensation/CPI) (·I) 6. LUCASPILIA* * Log(Total Annual Compensation/CPI) (·I) 6. LUCASPILIA* * Log(Total Annual Compensation/CPI) (·I) 6. APPLE * Log(Total Annual Compensat		Estimate		T-Value	
2. Conduct * (Log(Nay)^2 - Log(38)*2) 0.1644 *** 0.0582 2.8269 3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92) 0.0181 0.0397 0.4552 4. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0529 0.0451 1.1732 5. A DOBBE * Log(Total Annual Compensation/CPI) (-1) 0.7546 *** 0.0559 13.1734 6. A PPLE* * Log(Total Annual Compensation/CPI) (-1) 0.4415 *** 0.075 5.6953 8. INTEL * Log(Total Annual Compensation/CPI) (-1) 0.0441 *** 0.0343 19358 9. INTUIT * Log(Total Annual Compensation/CPI) (-1) 0.709** 0.0492 11.4179 10. LCASFILM * Log(Total Annual Compensation/CPI) (-1) 0.9794 *** 0.0794 11.5725 11. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.2370 *** 0.0822 4.0726 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2370 *** 0.082 4.0726 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.2370 *** 0.082 4.0726 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.2390 *** 0.0462 7.8171 15. INTEL * Log(Total Annual Compensa		(1)	(2)		
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92) 4. Conduct	1. Conduct * (Log Age - Log(38))	1.2212 ***	0.4445	2.7473	
4. Conduct -0.08529 0.0451 -1.1732 5. ADDBE* Log(Total Annual Compensation/CPI) (-1) 0.7366**** 0.0559 13.1734 6. APPLE** Log(Total Annual Compensation/CPI) (-1) 0.7366**** 0.0564 12.084 7. GOGGLE** Log(Total Annual Compensation/CPI) (-1) 0.4415**** 0.0755 5.0953 8. INTEL** Log(Total Annual Compensation/CPI) (-1) 0.7099*** 0.0492 1.44179 10. LUCASIFILM** Log(Total Annual Compensation/CPI) (-1) 0.7099*** 0.0492 1.44179 10. LUCASIFILM** Log(Total Annual Compensation/CPI) (-1) 0.7039*** 0.0492 1.44179 10. LUCASIFILM** Log(Total Annual Compensation/CPI) (-2) 0.22370**** 0.0582 4.0726 12. APPLE** Log(Total Annual Compensation/CPI) (-2) 0.2372**** 0.0582 4.0726 13. APPLE** Log(Total Annual Compensation/CPI) (-2) 0.2530**** 0.0466 5.7046 14. GOOGLE** Log(Total Annual Compensation/CPI) (-2) 0.2520**** 0.0028 10.508 15. INTLIT** Log(Total Annual Compensation/CPI) (-2) 0.2520**** 0.0028 10.508 16. INTLIT** Log(Total Annual Compensation/CPI) (-2) 0.02520***<	2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1644 ***	0.0582	-2.8269	
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	0.0181	0.0397	0.4552	
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	4. Conduct	-0.0529	0.0451	-1.1732	
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1) 0.4415 *** 0.0755 5.0953 8. INTEL * Log(Total Annual Compensation/CPI) (-1) 0.0647 *** 0.0343 19358 9. INTUIT * Log(Total Annual Compensation/CPI) (-1) 0.0919*** 0.0492 14.4179 10. LUCASFILM * Log(Total Annual Compensation/CPI) (-1) 0.0709*** 0.0794 11.5725 11. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.2370 *** 0.0582 4.0726 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2372 *** 0.046 5.704 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3639** 0.042 7.8717 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2820 **** 0.046 7.8717 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2527 *** 0.041 5.8777 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.080 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.080 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.080 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PI	5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.7365 ***	0.0559	13.1734	
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7546 ***	0.0624	12.0844	
9. INTUIT** Log(Total Annual Compensation/CPI) (-1) 0.0099*** 0.0492 14.4179 10. LUCASFILM** Log(Total Annual Compensation/CPI) (-1) 0.0194*** 0.0794 11.5725 11. PIXAR** Log(Total Annual Compensation/CPI) (-2) 0.2370*** 0.0582 4.0726 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2372**** 0.0462 7.8717 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.639*** 0.0462 7.8717 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2820**** 0.0268 10.508 16. INTUIT** Log(Total Annual Compensation/CPI) (-2) 0.2527**** 0.0431 5.8577 17. LUCASFILM** Log(Total Annual Compensation/CPI) (-2) 0.0510 0.084 0.6341 18. PEXAR** Log(Total Annual Compensation/CPI) (-2) 0.0510 0.084 0.6341 19. Log(Age) (Years) 0.0736**** 0.0278 3.3862 20. Log(Company Tenure) (Months) 0.0030 0.0453 -0.061 21. Log(Company Tenure) (Months) 0.0030 0.0453 -0.061 23. Male 0.0008 0.0047 0.1688 23. Male	7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4415 ***	0.0775	5.6953	
10. LUCASFILM* Log(Total Annual Compensation/CPI) (-1)	8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6847 ***	0.0343	19.9358	
10. LUCASFILM* Log(Total Annual Compensation/CPI) (-1)	9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.7099 ***	0.0492	14.4179	
11. PRXAR * Log(Total Annual Compensation/CPI) (-1) 0.7039 **** 0.1421 4.9544 12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.2372 **** 0.046 5.7640 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.3639 *** 0.0462 7.8717 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2820 *** 0.0268 10.5088 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0029 0.1131 0.8210 19. Log(Age) (Years) -0.7036 **** 0.2078 -3.3862 20. Log(Age) (Years) -0.0030 0.0453 -0.0661 21. Log(Company Tenure) (Months) -0.0030 0.0453 -0.0661 22. Log(Age) (Years) 0.0068 0.0007 0.0681 23. Male 0.0058 ** 0.0025 2.201 24. DLog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.6475 3.4424 25		0.9194 ***	0.0794	11.5725	
12. ADOBE * Log(Total Annual Compensation/CPI) (-2) 0.2370 **** 0.0582 4.0726 13. APPLE * Log(Total Annual Compensation/CPI) (-2) 0.2372 *** 0.046 5.7046 14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.2820 **** 0.0268 10.5038 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.2527 *** 0.0431 5.8577 17. LUCASFILM * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PEXAR * Log(Total Annual Compensation/CPI) (-2) 0.0029 0.1131 0.8210 19. Log(Age) (Years) -0.7036 *** 0.2078 -3.3862 20. Log(Age)*2 0.0030 0.0453 -0.0611 21. Log(Company Tenure) (Months) -0.0030 0.0453 -0.0616 22. Log(Company Tenure) (Months) -0.0058 ** 0.0025 2.3013 24. Diog(Information Sector Employment in San-Jose) * (I-INTEL) 1.0391 ** 0.0021 2.006 25. Diog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.6475 3.442 26. Diog(National Hardware Engineer Employment) * INTEL -0.3709 *** 0.0974 -3.807 27. Log(Total Number of Transfers Among Defendants) 0.0120	1 , , ,	0.7039 ***	0.1421	4.9544	
13. APPLE * Log(Total Annual Compensation/CPI) (-2)	1 , , , ,	0.2370 ***	0.0582	4.0726	
14. GOOGLE * Log(Total Annual Compensation/CPI) (-2) 0.3639 *** 0.0462 7.8717 15. INTEL * Log(Total Annual Compensation/CPI) (-2) 0.2527 *** 0.0281 10.508 16. INTUIT * Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0010 0.0804 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0029 0.1131 0.8210 19. Log(Age) (Years) 0.0051 ** 0.029 0.1131 0.8210 20. Log(Age)^2 0.0051 ** 0.005 0.045 3.2018 21. Log(Company Tenure) (Months) 0.0058 ** 0.0025 2.3013 23. Male 0.0058 ** 0.0025 2.3013 24. DLog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.647 3.4424 25. DLog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.675 3.4424 26. DLog(National Hardware Engineer Employment) * INTEL 2.2289 0.675 3.496 27. Log(Total Number of New Hires In the Firm/Number of Employees(-1)) 0.0599 0.0586 -1.0228 30. Log(Total Number of New Hires In the Firm/Number of Employees(-1)<	. , , , ,	0.2372 ***	0.0416	5.7046	
15. INTEL.* Log(Total Annual Compensation/CPI) (-2) 0.2820**** 0.0268 10.508 16. INTUTI** Log(Total Annual Compensation/CPI) (-2) 0.2527**** 0.0431 5.8577 71. ILUCASFILM* Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0029 0.1131 0.8210 19. Log(Age) (Years) 0.7036**** 0.026 3.3862 20. Log(Age)*2 0.00851*** 0.0264 3.2218 21. Log(Company Tenure) (Months) 0.0008 0.0047 0.1688 23. Male 0.0058 ** 0.0025 2.3013 24. DLog(Information Sector Employment in San-Jose) * (1-INTEL) 0.0058 ** 0.0025 2.3013 25. DLog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.6475 3.4442 26. DLog(National Hardware Engineer Employment) * INTEL 2.239 0.6475 3.4442 27. Log(Total Number of Transfers Among Defendants) 0.0743 ** 0.036 2.2780 28. Year (trend) 0.0059 0.0586 1.0228 30. Log(Total Number of New Hires) In the Firm/Number of Employees(-I) 0.0059 0.0586 1.0228		0.3639 ***	0.0462	7.8717	
16. INTUIT* LogTotal Annual Compensation/CPI) (-2) 0.2527*** 0.0431 5.8577 17. LUCASPILM* LogTotal Annual Compensation/CPI) (-2) 0.0010 0.0804 0.6341 18. PIXAR * LogTotal Annual Compensation/CPI) (-2) 0.0029 0.1131 0.8210 19. Log(Age) (Years) 0.7036*** 0.2078 3.3862 20. Log(Age) (Years) 0.0030 0.0453 -0.0661 21. LogCompany Tenure) (Months) 0.0008 0.0043 -0.061 22. LogCompany Tenure) 2 0.0008 0.0043 -0.061 23. Male 0.0008 0.005 2.3013 24. DLog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.6475 3.4424 25. DLog(National Hardware Engineer Employment) * INTEL 2.3709***** 0.0743 * 3.806 27. Log(Total Number of Transfers Among Defendants) 0.0743 ** 0.0326 2.2780 28. Year (trend) 0.0120 0.008 -1.0228 29. Log(Number of New Hires In the Firm/Number of Employees(-1)) 0.0894 0.0586 -1.0228 30. Log(Firm Revenue Per Employee/CPI) (-1) 0.0046 0.0581 0.0263 31. Log(Firm Revenue Per Employee/CPI) (-	. , , , ,	0.2820 ***	0.0268	10.5038	
17. LUCASFILM* Log(Total Annual Compensation/CPI) (-2) 0.0510 0.0804 0.6341 18. PIXAK* Log(Total Annual Compensation/CPI) (-2) 0.0929 0.1131 0.8210 19. Log(Age) (Years) -0.7036*** 0.2078 -3.3862 10. Log(Age)^2 0.0851 *** 0.0264 3.2281 1. Log(Company Tenure) (Months) -0.0030 0.0453 0.0661 12. Log(Company Tenure) (Months) -0.0030 0.0453 0.0661 12. Log(Company Tenure) (Months) -0.0008 0.0047 0.1688 12. Log(Company Tenure) (Months) -0.0008 0.0047 0.1688 12. Log(Company Tenure) (Months) -0.0008 0.005 0.005 0.005 0.0051 0.0051 0.0052		0.2527 ***	0.0431	5.8577	
18. PIXAR * Log(Total Annual Compensation/CPI) (-2) 0.0929 0.1131 0.8210 19. Log(Age) (Years) -0.7036*** 0.2078 -3.3862 20. Log(Age)^2 0.0851 *** 0.0264 3.238 21. Log(Company Tenure) (Months) -0.0030 0.0453 -0.061 22. Log(Company Tenure)^2 0.0008 0.0047 0.1688 23. Male 0.0058 ** 0.0025 2.3013 24. DLog(Information Sector Employment in San-Jose) * (1-INTEL) 1.0391 ** 0.5021 2.0096 25. DLog(Information Sector Employment) * INTEL 2.2289 0.6475 3.4424 26. DLog(National Hardware Engineer Employment) * INTEL 0.3709 *** 0.0974 -3.8067 27. Log(Total Number of Transfers Among Defendants) 0.0743 ** 0.0326 2.2780 28. Year (trend) -0.0120 0.0080 -1.4956 29. Log(Number of New Hires In the Firm/Number of Employees(-1)) -0.0599 0.0586 -1.022 20. Log(Firm Revenue Per Employee/CPI) (-1) 0.024 0.0781 0.2607 21. Log(Firm Revenue Per Employee/CPI) (-1) 0.0346 0.0582 1.6200 23. APPLE -0.0346		0.0510	0.0804	0.6341	
19. Log(Age) (Years)		0.0929		0.8210	
20. Log(Age)*2 0.0851 *** 0.0264 3.2218 21. Log(Company Tenure) (Months) -0.0030 0.0453 -0.061 22. Log(Company Tenure)*2 0.0008 0.0047 0.1688 23. Male 0.0058 ** 0.0025 2.3013 24. DLog(Information Sector Employment in San-Jose) * (1-INTEL) 1.0391 ** 0.5021 2.062 25. DLog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.6475 3.442 26. DLog(National Hardware Engineer Employment) * INTEL -0.3709 *** 0.0974 -3.8067 27. Log(Total Number of Transfers Among Defendants) 0.0743 ** 0.0326 2.2780 28. Year (trend) -0.0120 0.0080 -1.4956 29. Log(Number of New Hires In the Firm/Number of Employees(-1)) -0.0120 0.0080 -1.0228 30. Log(Firm Revenue Per Employee/CPI) (-1) 0.0204 0.0781 0.2607 31. Log(Firm Revenue Per Employee/CPI) (-1) 0.0946 0.0582 1.6260 32. NPLE -0.0346 0.2850 -0.1213 34. GOOGLE 1.3181 *** 0.4708 2.7998 35. INTEL -0.0447 0.2821 -0.1583					
21. Log(Company Tenure) (Months) -0.0030 0.0453 -0.0661 22. Log(Company Tenure)^2 0.0008 0.0047 0.1688 23. Male 0.0058 ** 0.0025 2.3013 24. Dlog(Information Sector Employment in San-Jose) * (I-INTEL) 1.031 ** 0.5021 2.0908 25. Dlog(Information Sector Employment in San-Jose) * INTEL 2.2289 0.6475 3.4424 26. Dlog(National Hardware Engineer Employment) * INTEL -0.3709 *** 0.0974 -3.8067 27. Log(Iotal Number of Transfers Among Defendants) 0.0743 ** 0.0326 2.2780 28. Year (trend) -0.0120 0.0080 -1.4956 29. Log(Iotal Number of New Hires In the Firm/Number of Employees(-1)) -0.0599 0.0586 -1.0228 30. Log(Total Number of New Hires In the Firm/Number of Employees(-1)) -0.0204 0.0781 0.2604 29. Log(Firm Revenue Per Employee/CPI) (-1) 0.0204 0.0781 0.2604 31. Log(Firm Revenue Per Employee/CPI) (-1) 0.0946 0.0582 -0.1213 34. GOOGLE 1.3181 *** 0.4708 2.7998 35. INTEL -0.0447 0.2821 -0.1583 36. INTUIT			0.0264	3,2218	
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1		YES			
Observations 277,082	R-Square	0.870			
	Observations	277,082			

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of
- employees, both obtained from SEC Filings. Lucasfilm and Pixar revenues obtained from defendant documents.
- (5) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (6) National Employment Statistics for Computer Hardware Engineer Occupation Category from BLS.
- (7) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings

Exhibit 11 - Model with Stock Prices and Profit for Publicly Traded Defendants

Observation: Employee ID record in December of each year Dependant Variable: Log(Total Annual Compensation/CPI)

	Robust		
Variable	Estimate	St. Error	T-Value
	(1)	(2)	(3)
			(1)/(2)
1. Conduct * (Log Age - Log(38))	0.9851 ***	0.4209	2.3408
2. Conduct * (Log(Age)^2 - Log(38)^2)	-0.1338 ***	0.0548	-2.4406
3. Conduct * (Log(Number of New Hires In the Firm/Number of Employees(-1)) + 1.92)	-0.0574	0.0404	-1.4193
4. Conduct	-0.1151 **	0.0551	-2.0901
5. ADOBE * Log(Total Annual Compensation/CPI) (-1)	0.6736 ***	0.0671	10.0345
6. APPLE * Log(Total Annual Compensation/CPI) (-1)	0.7357 ***	0.0612	12.0278
7. GOOGLE * Log(Total Annual Compensation/CPI) (-1)	0.4424 ***	0.0751	5.8917
8. INTEL * Log(Total Annual Compensation/CPI) (-1)	0.6782 ***	0.0365	18.5989
9. INTUIT * Log(Total Annual Compensation/CPI) (-1)	0.6231 ***	0.0614	10.1441
10. ADOBE * Log(Total Annual Compensation/CPI) (-2)	0.3002 ***	0.0562	5.3421
11. APPLE * Log(Total Annual Compensation/CPI) (-2)	0.2449 ***	0.0414	5.9186
12. GOOGLE * Log(Total Annual Compensation/CPI) (-2)	0.3704 ***	0.0432	8.5797
13. INTEL * Log(Total Annual Compensation/CPI) (-2)	0.2892 ***	0.0325	8.8998
14. INTUIT * Log(Total Annual Compensation/CPI) (-2)	0.3294 ***	0.0563	5.8550
15. Log(Age) (Years)	-0.6437 ***	0.1950	-3.3008
16. Log(Age)^2	0.0772 ***	0.0247	3.1227
17. Log(Company Tenure) (Months)	0.0051	0.0407	0.1250
18. Log(Company Tenure)^2	0.0001	0.0042	0.0197
19. Male	0.0051 **	0.0025	2.0700
20. DLog(Information Sector Employment in San-Jose)	1.9420 ***	0.4502	4.3137
21. Log(Total Number of Transfers Among Defendants)	0.1169 ***	0.0411	2.8417
22. Year (trend)	-0.0051	0.0103	-0.4932
23. Log(Number of New Hires In the Firm/Number of Employees(-1))	0.0702 *	0.0389	1.8052
24. Log(Total Number of New Hires)	-0.3719 ***	0.0560	-6.6385
25. Log(Firm Revenue Per Employee/CPI) (-1)	0.1251	0.1633	0.7662
26. DLog(Firm Revenue Per Employee/CPI) (-1)	0.2041 *	0.1051	1.9419
27. (Profit Per Employee/CPI) (-1)	-0.2517	0.1554	-1.6197
28. Log(Annual Average Stock Price/CPI)	0.0531	0.0456	1.1655
29. DLog(Annual Average Stock Price/CPI)	-0.0965	0.0895	-1.0786
30. APPLE	-0.0965	0.3258	-0.2963
31. GOOGLE	1.1236 **	0.5388	2.0853
32. INTEL	0.0675	0.2768	0.2440
33. INTUIT	0.0942	0.2133	0.4415
34. Location (State) Indicators	YES		
35. Constant	YES		
R-Square	0.875		
Observations	271,773		

Note: (1) *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

- (2) Total Annual Compensation is computed as sum of base annual compensation (in December), overtime pay, bonus, and value of equity compensation granted.
- (3) Value of equity compensation is computed using the weighted average grant-date fair values for stock options and restricted stock units from SEC Filings.
- (4) Firm Revenue Per Employee is computed as a ratio of global revenue to global number of employees, both obtained from SEC Filings.
- (5) Firm Profit Per Employee is computed as a ratio of global net income to global number of employees, both obtained from SEC Filings.
- (6) Firm Stock Prices obtained From Yahoo Finance
- (7) Observations are restricted to cases in which there was no change in employer in the previous two years.
- (8) Lucasfilm and Pixar omitted due to lack of data.
- (9) Standard Errors adjusted for clustering at employer-year level.

Source: Defendants' employee compensation data; St. Louis Fed Reserve; SEC Filings